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Drivers of $PM_{2.5}$ air pollution deaths in China 2002–2017

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Between 2002 and 2017, China's gross domestic product grew by 284%, but this surge was accompanied by a similarly prodigious growth in energy consumption, air pollution and air pollution-related deaths. Here we use a combination of index decomposition analysis and chemical transport modelling to quantify the relative influence of eight different factors on $PM_{2.5}$-related deaths in China over the 15-year period from 2002 to 2017. We show that, over this period, $PM_{2.5}$-related deaths increased by 0.39 million (23%) in China. Emission control technologies mandated by end-of-pipe control policies avoided 0.87 million deaths, which is nearly three-quarters (71%) of the deaths that would have otherwise occurred due to the country's increased economic activity. In addition, energy-climate policies and changes in economic structure have also became evident recently and together avoided 0.39 million deaths from 2012 to 2017, leading to a decline in total deaths after 2012, despite the increasing vulnerability of China's ageing population. As advanced end-of-pipe control measures have been widely implemented, such policies may face challenges in avoiding air pollution deaths in the future. Our findings thus suggest that further improvements in air quality must not only depend on stringent end-of-pipe control policies but also be reinforced by energy-climate policies and continuing changes in China's economic structure.

Rapid, energy-intensive and coal-fuelled economic growth in China[1] has substantially degraded air quality in the country[2], and the resulting impacts on human health have been a major source of concern for both the government and people of China. According to the Global Burden of Disease (GBD) study, population-weighted annual mean $PM_{2.5}$ concentrations in China rose from 48.5 to 58.4 μg m^{-3} between 1990 and 2015, corresponding to a similar increase in annual $PM_{2.5}$-related deaths from 0.95 to 1.11 million (ref. [3]).

In response to mounting public health risks, China has implemented a series of policies aimed at improving energy efficiency and decreasing energy-related pollution. Beginning in the country's 11th five-year plan (2005–2010), the government set a goal of reducing energy intensity (energy per unit gross domestic product (GDP)) by 20% and reducing SO_2 emissions by 10% between 2005 and 2010[4,5]. The 12th five-year plan (2010–2015) ramped up the ambition of these goals, targeting a 16% reduction in energy intensity and 8% and 10% of reductions in emissions of SO_2 and NO_x, which are major precursors of $PM_{2.5}$ pollution, respectively, by 2015[6,7]. Furthermore, in 2013, China implemented the first phase of the Air Pollution Prevention and Control Action Plan (hereinafter referred to as the 'Action Plan') to tackle the nationwide air pollution issue, with a series of emission control measures in different sectors[8]. Specifically, $PM_{2.5}$ concentrations over key regions such as Beijing and its surrounding area were required to decline by 15–25% before 2017[8–10].

However, although prior studies have assessed specific benefits of some of China's environmental and public health policies[9–13], it remains unclear how the effects of such policies have interacted with contemporaneous trends in the country's economic development, weather patterns and demographic characteristics, which may compete with or reinforce one another to determine the country's air pollution emissions, concentrations of $PM_{2.5}$ pollution and related mortality. Here we use a detailed sector-specific inventory of air pollutant emissions (the Multi-resolution Emission Inventory of China (MEIC))[10,14], index decomposition analysis[15], a chemical transport model (the Community Multi-scale Air Quality (CMAQ))[16] and the newly developed Global Exposure Mortality Model (GEMM)[17] to systematically analyse and compare the importance of eight different factors affecting premature deaths due to $PM_{2.5}$ pollution in China over the period 2002–2017: (1) economic growth (changes in GDP), (2) end-of-pipe control policy (changes in emissions per unit of consumed energy), (3) energy-climate policy (changes in both energy per unit GDP and the fuel mix of the energy sector), (4) economic structure (changes in the fractional contribution of GDP by different industry sectors), (5) interannual meteorological variation, (6) population growth, (7) population ageing (changes in the age structure of the population) and (8) improved health care (changes in baseline mortality rates independent of exposure to $PM_{2.5}$) (Extended Data Fig. 1). By coupling these data and models, we can consistently assess the relative influence of these factors on both pollution concentrations ("exposure" factors 1–5) and $PM_{2.5}$-related deaths (including the exposure factors 1–5 and "vulnerability" factors 6–8)[3] in China over the period 2002–2017. Details of our analytic approach are described in Methods and Supplementary Information.

Trends in socioeconomic and vulnerability factors

Figure 1 shows the trends in the main socioeconomic (or exposure) and vulnerability factors in China. Over 2002–2017, Chinese GDP

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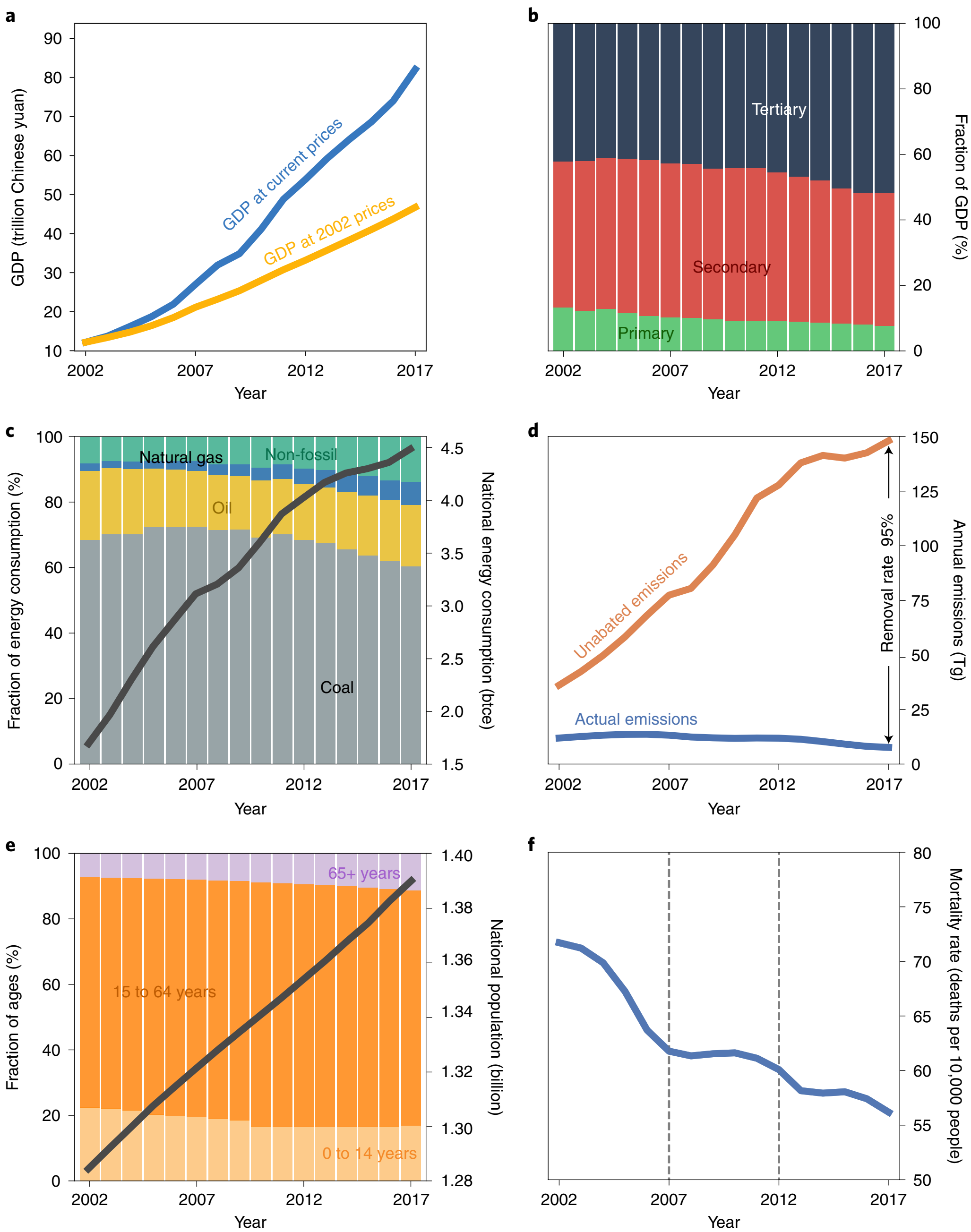

Fig. 1 | Trends in factors affecting air pollution emissions, exposure and vulnerability in China 2002–2017. a, National GDP at current and 2002 prices. **b**, Contribution of primary, secondary and tertiary industries to Chinese total GDP. **c**, National energy consumption and fractions of different fuels. **d**, Trends in actual and unabated primary $PM_{2.5}$ emissions in China. **e**, National population and fractions of different age groups. **f**, Age-standardized mortality rates (that is, weighted average of age-specific mortality rates based on the fixed age structure from a standard population) attributable to the sum of non-communicable diseases and lower respiratory infections in China.

grew at a mean annual rate of 9.4%, from 12.2 to 46.9 trillion CNY (in 2002 prices; Fig. 1a), with the contribution of tertiary industries increasing from 42.2% to 51.9% (Fig. 1b)[1]. Growth in the economy is likely to increase air pollution emissions, which can be partially offset by changes in economic structure. Meanwhile, China's total annual energy consumption grew at a mean annual rate of 6.7%, from 1.7 to 4.5 billion ton coal equivalent (btce) (Fig. 1c), to which the contribution from coal declined from 68.5% to 60.4%[1], indicating gains in energy efficiency (as compared with the growth of GDP) and efforts in reducing the share of coal. Rising air pollutant emissions triggered the implementation of end-of-pipe control policies. Taking primary $PM_{2.5}$ as an example, the removal rate surged from 67% to 95% during 2002–2017, demonstrating the efficacy of end-of-pipe control policies (Fig. 1d)[10]. Over the same period, the country's population increased at a mean annual rate of 0.53%, from 1.28 to 1.39 billion[1], toward an ageing structure (Fig. 1e). Meanwhile, the age-standardized mortality rate (that is, weighted average of age-specific mortality rates based on the fixed age structure of a standard population) of non-communicable diseases and lower respiratory infections (two disease endpoints representing the mortality burden of $PM_{2.5}$ exposure[17]) in China reduced from 72 to 56 deaths per 10,000 people per year, at a

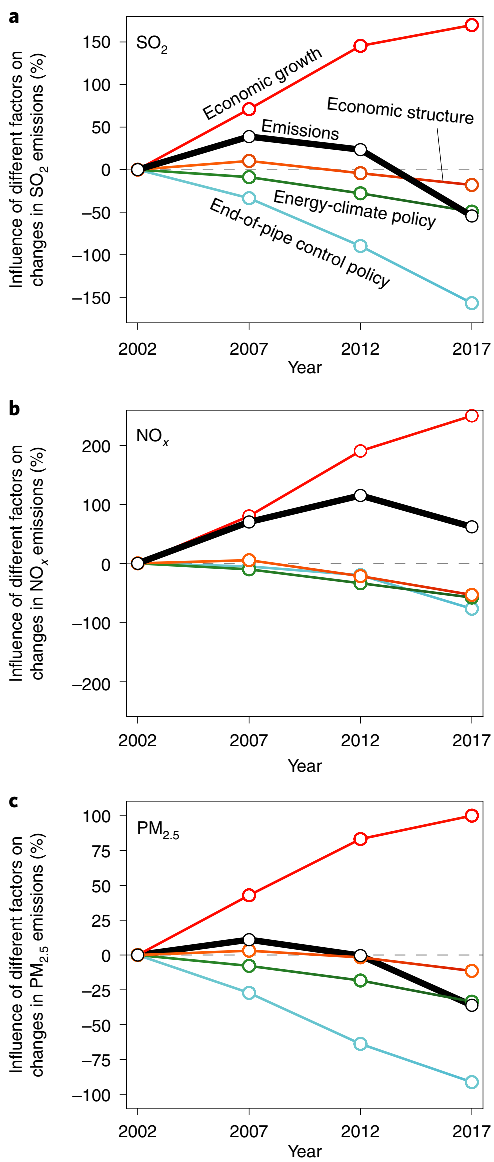

Fig. 2 | Economic and policy drivers of major air pollutant emissions in China 2002–2017. a–c, SO_2 (**a**), NO_x (**b**) and primary $PM_{2.5}$ (**c**) emissions. Black lines represent the actual emissions. Red, orange, green and blue lines represent emissions driven by economic growth, economic structure, energy-climate policy and end-of-pipe control policy, respectively.

continuously slowing decreasing pace (Fig. 1f)[18], reflecting improved health care in China including better medical services and healthier human behaviours. Population will be more vulnerable to air pollution exposure when the ageing population outweighs the decreased age-standardized baseline mortality rate. The combined effects of the described factors drive the trend of China's air pollution emissions, exposure and population vulnerability.

Drivers of air pollutant emissions

Figure 2 shows emission trends of SO_2, NO_x and $PM_{2.5}$ in China during 2002–2017 (black curves) and the relative influence of the four socioeconomic drivers on these emissions. During the entire 15-year period, economic growth is the main driver of emission increase (red curves), while end-of-pipe control policies (that is, policies that mandated end-of-pipe control technologies and/or promoted low-emission technologies; blue curves) have effectively restrained comparable emission growth. Energy-climate policies (that is, those primarily aimed at altering the fuel mix of the energy sector and improving energy efficiency; green curves) and changes in economic structure (orange curves) also helped reduce emissions, but with relatively limited effects in earlier years and increasing contributions at the end of the time period.

Emissions of all three pollutants increased from 2002 to 2007 (by 38.9%, 70.4% and 11.1%, respectively), driven primarily by rapid economic growth and relatively weak control policies. Although increases in emissions of SO_2 and $PM_{2.5}$ were partially restrained by end-of-pipe control policies[19,20], NO_x emissions increased rapidly because effective control measures were absent during that period (Extended Data Table 1). The effects of energy-climate policies were also limited as the share of energy from coal increased (Fig. 1c). Between 2007 and 2012, those trends in economic growth, end-of-pipe control policy and energy-climate policy continued, but total emissions of SO_2 and $PM_{2.5}$ decreased by 11.0% and 10.3%, respectively, primarily benefitting from more effective emission reduction efforts (that is, end-of-pipe control policy). Also underlying this reversal were changes in economic structure, which became a downward influence on emissions (Fig. 2a,c; also see changing shares of emissions from major industry sectors in Extended Data Fig. 2). Although NO_x-specific policies were implemented in 2010 (with a targeted national emission cap; Extended Data Tables 1 and 2), limited deployment of control technologies before 2012 led to a 26.5% increase in NO_x emissions between 2007 and 2012 (Extended Data Tables 1 and 2)[10,20]. In the most recent period (2012–2017), even more stringent end-of-pipe control policies (part of the Action Plan) were implemented to mitigate severe air pollution (Extended Data Table 1)[9,10,21]. At the same time, both energy-climate policies and shifts in the country's economic structure contributed to more evident decreases in emissions of all three pollutants than in the previous sub-periods (Extended Data Table 1)[10]. Combining all the policy factors together, large net reductions were obtained in emissions of SO_2, primary $PM_{2.5}$ and NO_x, with reduction ratios of 63.2%, 35.8% and 24.8%, respectively, during 2012–2017 (Fig. 2; Extended Data Table 1)[9,10].

Drivers of $PM_{2.5}$ exposure and related deaths

As a consequence of emission changes, national population-weighted annual mean $PM_{2.5}$ concentrations increased from 51.5 μg m^{-3} (95% CI 46.6–61.7 μg m^{-3}) to 63.6 μg m^{-3} (95% CI 57.8–76.0 μg m^{-3}) between 2002 and 2007, then declined to 42.1 μg m^{-3} (95% CI 38.3–50.3 μg m^{-3}) in 2017 (Fig. 3a, black bars). Trends in premature deaths attributable to $PM_{2.5}$ exposure during the same period are presented in Fig. 3b. These trends in $PM_{2.5}$ exposure and premature deaths largely mirror the above-discussed trends in emissions, with generally consistent influences from each of the socioeconomic factors (Fig. 3). A noteworthy exception to this consistency is economic structure; although changes in the proportions of industrial sectors tended to increase emissions during 2002–2007, they nonetheless reduced average $PM_{2.5}$ exposure and related deaths because of geographical differences in the industries and exposed population (Extended Data Fig. 3).

Since 2007, strengthened end-of-pipe control and energy-climate policies have offset effects of economic growth and led to a reversing trend in $PM_{2.5}$ exposure. The largest reductions in $PM_{2.5}$ exposure and related deaths were achieved by the combined contributions of strict end-of-pipe control policies, energy-climate policies and policy-mandated adjustment of economic structure between 2012–2017, when the toughest-ever clean air actions in China (that is, the Action Plan) were implemented[9]. As a consequence, the net effects of changes in economic and policy factors (together labelled "Exposure") was to increase air pollution-related deaths by 221,000 (95% CI 172,000–267,000) between 2002 and 2007, then decrease deaths by 48,000 (95% CI 36,000–59,000) between 2007 and 2012,

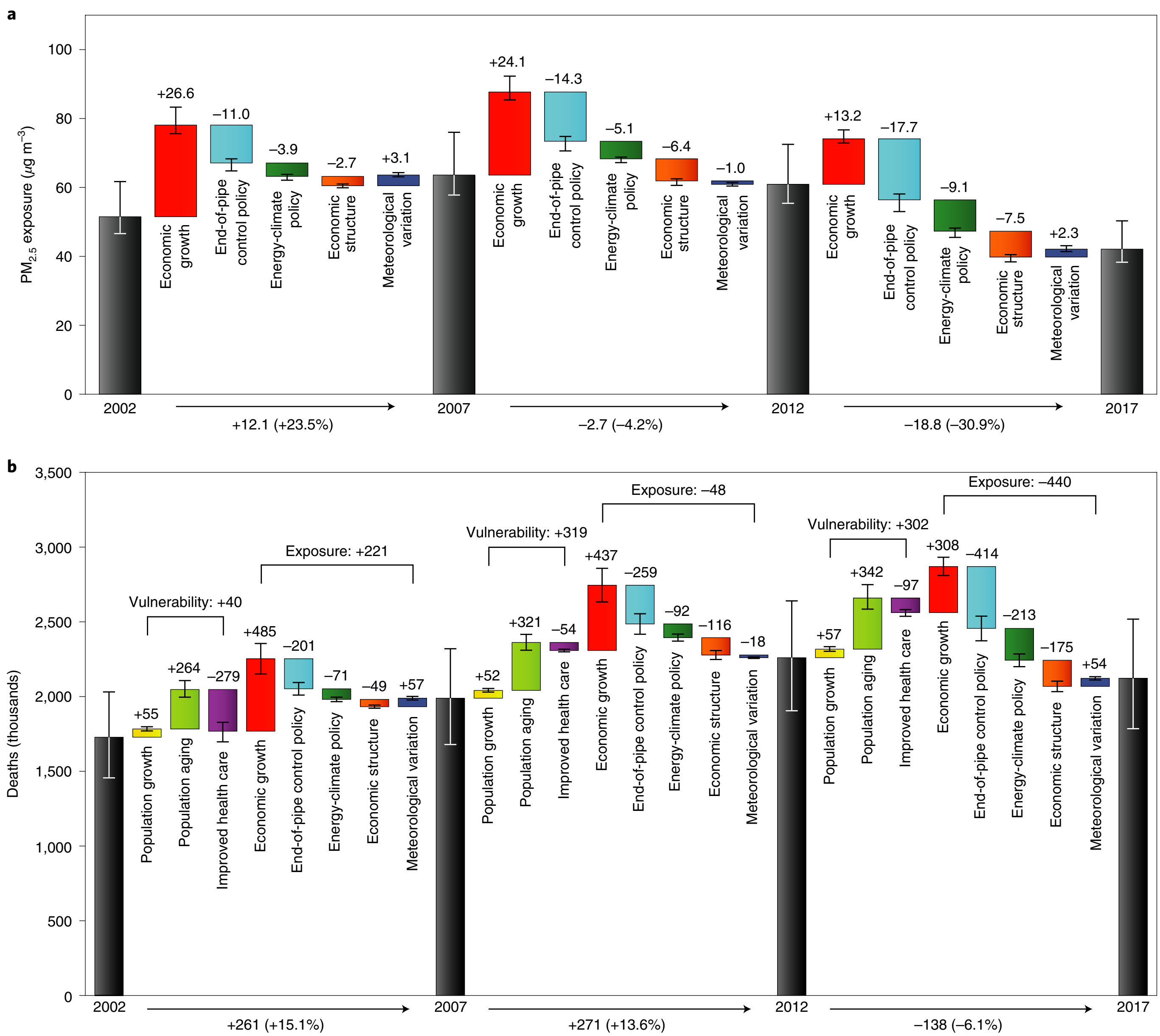

Fig. 3 | Drivers of changes in $PM_{2.5}$ exposure and associated mortality 2002–2017. a, Drivers of national population-weighted annual mean $PM_{2.5}$ concentrations over China. **b**, Drivers of national $PM_{2.5}$-related premature mortality. Error bars show the 95% CI of our estimates.

before decreasing deaths by 440,000 (95% CI 351,000–513,000) in the final five-year period of 2012–2017 (Fig. 3b).

Besides varying pollutant emissions, interannual changes in meteorological conditions, natural emission sources and population distribution (for example, due to migration and varying population growth rates in different regions) might have affected $PM_{2.5}$ exposure. Although meteorological conditions were favourable in the winter of 2012 and unfavourable in the winter of 2007 and 2017 compared with the corresponding start year of each sub-period (Extended Data Fig. 4), this had a relatively small effect on pollution exposure and deaths (Fig. 3, dark-blue bars). Natural emission sources, including windblown dust and biogenic emissions, make a relatively small contribution to $PM_{2.5}$-related deaths and show insignificant or marginal trends during the study period, thus not being major drivers of $PM_{2.5}$ exposure and death trends over China[22–25] during the study period. However, their relative influence will continue to grow as China tackles anthropogenic emissions, and their impacts should be considered especially for the cost–benefit assessment of future emission abatement policies. Changes in the population distribution had very little effect on population-weighted annual mean $PM_{2.5}$ concentrations (less than 0.3 μg m^{-3} for each 5-year period) and were thus neglected (Extended Data Table 3).

$PM_{2.5}$-related deaths were also affected by changes in population size, population age distribution and health care (together labelled "Vulnerability" in Fig. 3b) in China during 2002–2017. Increases in mortality due to ageing of the Chinese population (Fig. 3b, light-green bars) were comparable in size to the increases and decreases due to economic growth and end-of-pipe control policies, respectively (Fig. 3b, red and blue bars). Population vulnerability remained stable during 2002–2007 because the improved health care in China largely cancelled out the adverse effects of a growing and ageing population. However, health care improvements were much more limited over the latter two periods, leading to a continuously increased vulnerability during 2007–2017

(Figs. 1f and 3b). On net, we estimate that changes in population size, age and health care increased mortality related to air pollution in China throughout the whole period (Fig. 3b), which is consistent with previous studies[3].

Taking the combined influence of all factors, we estimate that premature deaths attributable to $PM_{2.5}$ exposure increased from 1.73 million people per year in 2002 (95% CI 1.46–2.03 million) to 2.26 million in 2012 (95% CI 1.91 to 2.64 million) and then slightly decreased to 2.12 (95% CI 1.79–2.52) million in 2017 (Fig. 3b, black bars). The estimated premature deaths in 2017 are comparable to other studies using the same GEMM model (for example, 2.42–2.47 million in 2015[17,26]). Our results show that economic growth in China was the primary driver of pollution emissions, poor air quality and related mortality between 2002 and 2017, but that the ageing of the Chinese population also substantially increased premature deaths due to air pollution. End-of-pipe control policies have been remarkably effective in countering rising emissions and related deaths over the same time period. However, energy-climate policies and changes in China's economic structure have become increasingly important over time. Indeed, the largest decreases in $PM_{2.5}$-related deaths over the period 2012–2017 were the result of coordinated policy efforts to control pollution, shift energy sources and adjust the country's economic structure[9].

The emerging role of energy-climate policy

Our findings are instructive for future policy-making. Although $PM_{2.5}$ concentrations decreased during 2002–2017, the national population-weighted annual mean $PM_{2.5}$ concentrations in 2017 (that is, 42.1 μg m^{-3}) still exceeds the air quality guideline of 10 μg m^{-3} proposed by the World Health Organization. Based on the combined effects of the three vulnerability factors (Fig. 3b), the Chinese population is increasingly vulnerable to air pollution. More than three decades of the "one-child" policy along with improvements in health care have contributed to low birth rates and longer life expectancy in China, resulting in an ageing population (Fig. 1e). Population growth is slowing and is thus unlikely to be a major driver of air pollution exposure in the future[27]. However, population ageing will continue to exacerbate air pollution deaths as the fraction of older people in China rises to that of other developed countries such as Japan and the United States[27]. Given that the improved health care failed to offset the adverse impacts from growing and ageing population during the investigated period (Figs. 1f and 3b), future vulnerability may continue to be a factor increasing premature mortality in China[3,18], which requires further strengthened emission reduction measures to protect public health.

Meanwhile, although China's economic growth has slowed in recent years, steady and robust growth is anticipated[28]. Given the effectiveness of end-of-pipe controls, a major question is whether such policies can continue to reduce emissions in the future. Substantial emission reductions during 2012–2017 mainly benefitted from strict end-of-pipe control measures by the implementation of the Action Plan. As of 2017, air pollution control technologies installed in China have achieved sector-average removal efficiencies of 76% and 95% for SO_2 and $PM_{2.5}$ emissions, respectively (see, for example, Fig. 1d and Extended Data Fig. 5). Specifically, the implementation of ultra-low emission standards for coal-fired power plants has achieved 93% and 98% removal efficiencies for SO_2 and $PM_{2.5}$ emissions in the power sector, respectively[10]. Future opportunities for controlling SO_2 and $PM_{2.5}$ emissions may still exist in small industries (for example, brick production, casting industry, etc.) and residential sectors, where it is difficult to implement highly efficient end-of-pipe control facilities. On the other hand, the average removal efficiency of NO_x emissions remained quite low (that is, 23%; Extended Data Fig. 5), and emissions of non-methane volatile organic compounds (NMVOCs) and NH_3 were nearly uncontrolled until 2017[9,10]. Therefore, the major emission reduction potentials by end-of-pipe control policies are for NO_x, NMVOCs and NH_3 emissions. It is worth noting that the absence of NMVOC control measures may have contributed to the increase in O_3 pollution in China under the VOC-limited condition during the past[29]. In the future, tailored control measures targeting emissions of both NO_x and NMVOCs would be beneficial for controlling $PM_{2.5}$ and O_3 pollution at the same time[30]. In particular, the limited effect of end-of-pipe control policies on NO_x abatement to date has been largely due to the high emissions from industrial combustion facilities and diesel trucks[10], which require stricter emission standards. Reducing emissions of NMVOCs and NH_3 is much more difficult due to the majority of small and scattered sources and low removal efficiency of current control technologies. All of this suggests that end-of-pipe control policies may face challenges in avoiding air pollution deaths in the future.

Thus, although energy-climate policies and changes in economic structure made relatively modest contributions before 2017, the increasing contribution of energy policies and shifting economic structure during 2012–2017 suggests that such energy-climate policies may be critical levers to protect public health in the future. Coal still dominates the Chinese energy sector, supplying 68.5% and 60.4% of energy in 2012 and 2017. But non-fossil energy including hydroelectric, nuclear, solar and wind power grew steadily from 2002 to 2017 (from 8.2% to 13.8% of total primary energy consumption; Fig. 1c), and as part of the Paris Agreement, China has committed to obtaining 20% of its energy from non-fossil sources by 2030[31], More ambitious efforts to decarbonize the Chinese energy sector and continue the shift away from coal could play an important role in improving air quality in the country. Similarly, the ongoing transition of the Chinese economy away from energy-intensive manufacturing and towards high-value-added assembly and service sectors may also greatly reduce air pollutant emissions and related deaths[32]. Indeed, the percentage of the country's GDP related to manufacturing has decreased in recent years, from 45.4% in 2012 to 40.5% in 2017[1].

Having quantified the major drivers of Chinese air pollution and related deaths during the past, we see signs that what has worked to reduce emissions and mortality in the past may be less effective in the future. Strengthening energy-climate policy can directly benefit air quality and public health in China. Climate change mitigation could bring wider health benefits beyond air quality improvement (for example, reducing extreme weather events, preventing disease transmission, protecting food supply, etc.)[33–37], and emerging and active climate actions may allow China to protect public health more effectively.

Online content

Any methods, additional references, Nature Research 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/s41561-021-00792-3.

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Methods

Integrated modelling framework. Models and data from multiple scientific disciplines and sources are integrated in this study to quantify the contributions of major drivers to the trend in premature deaths related to $PM_{2.5}$ pollution in China from 2002 to 2017 (Extended Data Fig. 1). The trends in $PM_{2.5}$-related deaths are decomposed into effects from eight drivers: (1) economic growth, (2) end-of-pipe control policies, (3) energy-climate policies, (4) economic structure, (5) meteorological variation, (6) population growth, (7) population ageing and (8) improved health care. The first five are factors related to $PM_{2.5}$ exposure levels ("exposure" factors), whereas the last three are factors related to the vulnerability of the population ("vulnerability" factors). The influences of each driver are estimated over three sub-periods: 2002–2007, 2007–2012 and 2012–2017. Four approaches are integrated, including the MEIC model, the logarithmic mean Divisia index (LMDI) approach, the CMAQ model and the exposure response functions from the GEMM model. Datasets used in this study include detailed bottom-up emission inventory of major air pollutants and the underlying statistics obtained from the MEIC model; socioeconomic statistics including sectoral GDP (that is, value added), price index and population from official national and provincial statistical yearbooks and datasets;[1,38–42] and national public health statistics including population structure and baseline mortality rate from the GBD study[18]. A full version of the methods applied with a detailed description of the models and datasets used in this study is provided in Supplementary Information, while a condensed version is provided below.

Anthropogenic emission inventory of major air pollutants. Anthropogenic emissions of SO_2, NO_x, CO, NH_3, primary $PM_{2.5}$, primary PM_{10} and NMVOCs are obtained from the MEIC model (http://www.meicmodel.org/)[10,14] to feed the emission decomposition and air quality simulations. The MEIC model is a bottom-up emission inventory model that provides detailed estimates of anthropogenic emissions of major air pollutants from more than 700 sources, covering both energy consumption and non-energy processes, over 31 provinces in Mainland China. Emissions of each air pollutant were calculated using the equation

$$E_p = \sum_s \sum_f A_{s,f} \times \mathrm{EF}_{p,s,f} \times (1 - \eta_{p,s,f}) \tag{1}$$

where p, s and f represent the air pollutant species, emitting sector, and fuel or product type, respectively. A is the activity rate, such as fuel consumption or material production. EF represents the unabated emission factor, which is emissions per unit fuel consumed or product produced. η represents the removal efficiency of end-of-pipe control technologies with typical values of η summarized in Supplementary Table 1. Details of the technology and process-based emission estimation approach, source classifications, and sources of the underlying data applied by the MEIC model are summarized elsewhere[10,14]. Both the emission estimates and the underlying statistics used to compile the emission inventory such as activity rates are obtained and serve as the base information for the decomposition of drivers behind the emission trends.

Decomposing drivers of air pollutant emission trends from 2002 to 2017. Detailed air pollutant emissions and other socioeconomic statistics are required as input data for the decomposition of emission trends. Emissions from detailed source categories at provincial level for the years 2002, 2007, 2012 and 2017 are directly collected from the MEIC model, as well as the corresponding activity rates (that is, fuel consumption or material production). The activity rates in the MEIC model are compiled originally based on China's official energy statistics[10,14]. Provincial non-thermal electricity generations, which are absent from the MEIC model, are collected from China Energy Statistical Yearbooks[43]. Other required socioeconomic statistics including sectoral GDP, price index and population are collected or compiled based on official national and provincial statistical yearbooks and datasets[1,38–42]. In this study, anthropogenic emissions of major air pollutants are attributed to 31 sectors (Supplementary Table 2), including 29 commercial subsectors and non-commercial urban and rural residential sectors. Details of the sector mapping process between different datasets can be found in Supplementary Table 2 and Supplementary Methods.

Based on the data retrieved above, the LMDI approach[15] is then used to decompose the effects of socioeconomic factors on the trends in air pollutant emissions. To facilitate the decomposition process, air pollutant emissions from the 31 final sectors are categorized into three source groups: energy consumption in the 29 commercial subsectors ($\mathrm{Emis}_{\mathrm{ene}}$), non-energy processes in the 29 commercial subsectors ($\mathrm{Emis}_{\text{non-ene}}$) and energy consumption in the two non-commercial residential sectors ($\mathrm{Emis}_{\mathrm{res}}$), as shown in equation (2):

$$\mathrm{Emis}_{\mathrm{total}} = \mathrm{Emis}_{\mathrm{ene}} + \mathrm{Emis}_{\text{non-ene}} + \mathrm{Emis}_{\mathrm{res}} \tag{2}$$

Emissions from these three source groups can be expressed as the products of several factors as shown in equations (3–5):

$$\mathrm{Emis}_{\mathrm{ene}} = \sum_s \sum_f \frac{\mathrm{Emis}_{s,f}}{N_{s,f}} \frac{N_{s,f}}{N_s} \frac{N_s}{G_s} \frac{G_s}{G} \frac{G}{P} P = \sum_s \sum_f U_{s,f} F_{s,f} I_s Y_s Q P \tag{3}$$

$$\mathrm{Emis}_{\text{non-ene}} = \sum_s \frac{\mathrm{Emis}_s}{G_s} \frac{G_s}{G} \frac{G}{P} P = \sum_s U_s Y_s Q P \tag{4}$$

$$\mathrm{Emis}_{\mathrm{res}} = \sum_s \sum_f \frac{\mathrm{Emis}_{s,f}}{N_{s,f}} \frac{N_{s,f}}{N_s} \frac{N_s}{P_s} P_s = \sum_s \sum_f U_{s,f} F_{s,f} I_s P_s \tag{5}$$

where s and f denote source sector and fuel type, respectively; Emis, N, G and P represent emissions, energy consumption, economic output (that is, GDP) and population, respectively. Specifically in equation (5), P_s means the urban population for the urban residential sector or the rural population for the rural residential sector. U is the emission efficiency, which is defined as unit emission per energy consumption in equations (3) and (5) and unit emission per GDP in equation (4). F is the fuel-specific contribution to total energy consumption, which represents the fractional contribution of specific energy consumptions to the total energy consumption. I is the energy intensity, which reflects energy consumption per GDP obtained in equation (3) and energy consumption per capita in equation (5). Y is the sectoral economic contribution, which represents the fractional contribution of GDP obtained in a specific commercial sector to the total GDP, and Q represents economic affluence, which is per capita GDP obtained.

Impacts of factors on emission variations of each pollutant over 30 provinces (Tibet, Macao, Hong Kong and Taiwan are excluded due to the lack of input data) are then quantified using the LMDI approach. Because the results of LMDI decomposition are additive, aggregated impacts of each factor on emission variations are summed from the sector- and fuel-specific decomposition results from different source groups at provincial level. Nationally aggregated decomposition results are directly summed from the provincial-level results. Based on the physical concept of each factor and to reduce the computing resources required in the following air quality modelling procedure, factors in equations (3–5) are combined. The impact of emission efficiency improvements (U) is regarded as end-of-pipe control policy effect (factor 2). Impacts of changes in energy structure (F) and energy intensity (I) are considered together as energy-climate policy effect (factor 3). Impact of economic structure adjustment (Y) is regarded as economic structure effect (factor 4). Impacts from economic growth (Q) and changes in population (P) are considered together as economic growth effect (factor 1). Emission trends during each sub-period are determined as inputs for the following air quality modelling.

Estimating contributions of the drivers to $PM_{2.5}$ concentration trends. The CMAQ model version 5.0.1 (ref. [16]) driven by the Weather Research and Forecasting model (WRF)[44] v3.5.1 is applied to simulate China's $PM_{2.5}$ concentrations from 2002 to 2017 and to isolate the contributions from the four socioeconomic factor as well as meteorological variation. The model is at a spatial resolution of 36 km, and the model configuration follows our previous studies[45,46]. Driven by initial and boundary conditions provided by the National Centers for Environmental Prediction Final Analysis reanalysis data, the WRF model provides simulated meteorological parameters as inputs to the CMAQ model. The CMAQ model is configured with CB05 as the gas-phase mechanism, AERO6 as the aerosol module and Regional Acid Deposition Model (RADM) as the aqueous-phase chemistry module. Boundary conditions for the CMAQ model are provided by the global GEOS-Chem model[47] at a spatial resolution of $2° \times 2.5°$. In the CMAQ model, anthropogenic emissions for Mainland China are derived from the MEIC model. Emissions beyond Mainland China are obtained from the MIX Asian emission inventory[48] and are fixed at the 2010 levels for all baseline and perturbation scenarios. Biogenic emissions for CMAQ simulation are calculated by the Model of Emissions of Gases and Aerosols from Nature (MEGAN) v2.1 (ref. [49]). Other emission sources, including sea salt[50] and natural dust[51], are calculated online by the CMAQ model.

Simulated meteorological parameters and surface $PM_{2.5}$ concentrations for the four base years are evaluated against surface observations (Supplementary Tables 4 and 5 and Figs. 1–3). The performance of the WRF model evaluated against observations has comparable performance to the benchmark metrics suggested based on various simulations in the eastern United States with 4–12 km grid resolutions on hourly basis[52]. The simulated $PM_{2.5}$ in China (mean fractional bias −34.2%, mean fractional error 59.8%) are also within the criteria limits (±60% and 75%, respectively) on daily basis suggested by the US Environmental Protection Agency[53]. Comparison between modelled and observed $PM_{2.5}$ observations in 2017 suggests that our model has a contrasting performance between eastern and western China. The model tends to underestimate $PM_{2.5}$ concentrations in the western part of China where population is sparse, but have quite good performance ($R = 0.75$, normalized mean bias −5.3%) in the eastern part of China where about

93.4% of the national population lives. Given that the population is mostly in eastern China and our study mainly focuses on the drivers of $PM_{2.5}$-related deaths, the underestimation of $PM_{2.5}$ concentrations in the western part of China is not likely to change our conclusions. The underestimation of $PM_{2.5}$ in urban areas in eastern China might be related to the overestimation of wind speed, as buildings and other human-made obstacles act as a momentum sink that considerably limits the advection of pollutants, which is not considered in a mesoscale model such as WRF, unless an urban parameterization is applied.

We also compared our model simulations with machine learning (ML)-based surface $PM_{2.5}$ estimates[54] (Supplementary Table 6 and Fig. 4). The ML-based $PM_{2.5}$ data are estimated using ML models with high-dimensional expansion of numerous predictors, including satellite aerosol optical depth and other satellite covariates, meteorological variables, etc. More details about the methodology to retrieve ML-based $PM_{2.5}$ data can be found elsewhere[54]. The ML-based $PM_{2.5}$ data have an R of 0.83 compared with ground observations on annual basis. Compared with ML-based $PM_{2.5}$ data in the four years, the simulated $PM_{2.5}$ concentrations over the eastern part of China correlate reasonably well with ML-based data with R values ranging from 0.87 to 0.92 between years. The normalized mean bias between population-weighted $PM_{2.5}$ from CMAQ simulations and ML-based data are between −5.6% and −3.5%. Because of the lack of observations in the early period before 2013, we use the ML-based $PM_{2.5}$ dataset to evaluate the trends of CMAQ simulations, which may introduce some uncertainties. It is worth noting that the uncertainties in $PM_{2.5}$ simulation could then propagate to health impact assessment and introduce uncertainties in premature mortality estimates. More discussion about the model evaluation can be found in Supplementary Methods.

We use a 'Fix emission' scenario to quantify the impacts of interannual meteorological variations on $PM_{2.5}$ concentrations by fixing anthropogenic emissions at the levels of the first year of each sub-period (Supplementary Table 3). Another commonly used method to quantify the impacts of meteorological variations on $PM_{2.5}$ trends are the statistical models based on continuous ground observations. The statistical-model-based approach performs better in providing empirical relationships between individual meteorological parameters with $PM_{2.5}$ concentrations, which facilitates understanding of the processes affecting pollutant concentrations. However, such a method is not suitable in China before 2013 when ground observations are unavailable. Previous studies have reported that both approaches have similar conclusions when applied in China after 2013[55–57], indicating that the CMAQ-based approach is valid and robust. More discussion about these two approaches and sensitivity tests regarding the non-linear effects from the CMAQ-based approach are provided in Supplementary Methods.

The impacts of other factors on $PM_{2.5}$ concentrations are quantified using the CMAQ model with the brute-force method. Four groups of perturbation scenarios are designed to quantify the impacts of economic growth, end-of-pipe control policies, energy-climate policies and economic structure adjustment on surface $PM_{2.5}$ concentrations, as summarized in Supplementary Table 3. Impacts of each factor during the three sub-periods (2002–2007, 2007–2012 and 2012–2017) are quantified separately, with perturbation simulations conducted for each factor in the years 2007, 2012 and 2017. Detailed descriptions of the emission scenarios and the calculation equations are provided in Supplementary Methods.

Mortality estimation and decomposition. Premature mortality attributable to $PM_{2.5}$ exposure is quantified using the newly developed GEMM model[17]. GEMM is built for estimating $PM_{2.5}$-related non-accidental mortality due to non-communicable diseases and lower respiratory infections (NCD+LRI). GEMM NCD+LRI parameterizes the dependence of relative risk (RR) of NCD+LRI on concentration (C) as

$$\mathrm{RR}\,(C) = e^{\frac{\theta \times \ln\left(\frac{z}{\alpha}+1\right)}{1+e^{\left(-\frac{z-\mu}{\nu}\right)}}},\ \text{where}\ z = \max(0, C - 2.4) \quad (6)$$

where θ, α, μ and ν determine the shape of the $PM_{2.5}$–mortality relationships. According to the GEMM framework, the RR of NCD+LRI is calculated by age for adults aged from 25 to greater than 85 years in 5-year intervals. The attributable fraction (AF) of mortality to $PM_{2.5}$ exposure can be further calculated as

$$\mathrm{AF}\,(C) = \frac{\mathrm{RR}\,(C) - 1}{\mathrm{RR}(C)} \quad (7)$$

The premature mortality (M) attributable to $PM_{2.5}$ exposure for a population subgroup s (population by age and gender) in grid j is further calculated as

$$M_{s,j}(C_j) = P_j \times PS_s \times B_s \times \mathrm{AF}_s(C_j) \quad (8)$$

where P_j represents the total population amount in grid j, PS_s represents the national fraction of a population subgroup s to the total population, B_s represents the national baseline mortality incidence rate of NCD+LRI for population subgroup s and $\mathrm{AF}_s(C_j)$ is the attributable fraction of NCD+LRI to $PM_{2.5}$ exposure at level C_j for population subgroup s.

According to equation (8), $PM_{2.5}$-attributable premature mortality is determined by four quantifiable variables and the changes in these variables contribute to the changes in $PM_{2.5}$-related mortality. Following the GBD approach[3], we quantify impacts from the changes in each of these four factors on the changes in premature mortality during each of the three sub-periods based on a series of sensitivity analyses that estimate the contribution from each factor incrementally. Technically, the decomposition with four factors in equation (8) has 24 decomposition sequences, and the mean value of the impact of each factor through all 24 sequences is calculated.

The net change in mortality contributed by changes in $PM_{2.5}$ exposure (ΔME) is further disaggregated into contributions from five factors related to exposure variations ("exposure" factors) decomposed previously. By multiplying fractional contribution of an "exposure" factor to $PM_{2.5}$ variations to ΔME, contributions of the factor to changes in mortality can then be derived. More details could be found in Supplementary Methods.

Uncertainties and limitations. Our study is subject to a number of uncertainties and limitations due to the use of a complex model framework. Uncertainties are discussed and quantified for each step in Supplementary Methods, and the overall uncertainty ranges (95% CI) associated with $PM_{2.5}$ exposure and mortality estimates are presented in Fig. 3. First, bottom-up emission inventory has uncertainties due to incomplete knowledge on activity rates, combustion and production technologies and emission factors[19,58,59]. The MEIC model has been widely applied in air quality simulations, and simulations are evaluated against surface and satellite-based observations[60–62]. Second, the LMDI approach introduces no uncertainties mathematically as the decomposition results do not contain residual terms[15]. Although the use of different decomposition methods might generate different decomposition results, the LMDI is regarded as the most preferred index decomposition analysis method due to its theoretical foundation, adaptability and ease of use and result interpretation[63]. Third, $PM_{2.5}$ concentrations simulated by the WRF/CMAQ model are also subject to uncertainties due to the model's imperfect representation of chemical and physical processes[60]. We compare the modelled $PM_{2.5}$ with ground observations and ML-based surface $PM_{2.5}$ estimates[54], finding reasonable agreements for densely populated regions in China. The normalized mean bias of our simulated national population-weighted annual mean $PM_{2.5}$ concentrations is about 5% as compared with the ML-based estimates. Last but not least, uncertainties in $PM_{2.5}$-related death estimates mainly come from the limited epidemiology evidence and statistical estimation of the GEMM model[17]. The overall uncertainties in $PM_{2.5}$ exposure and premature mortalities are calculated by Monte Carlo simulations that integrate errors in WRF/CMAQ simulations and errors in GEMM exposure-response function together. The error bars are presented in Fig. 3, and details are available in Supplementary Methods. The uncertainty estimates should be regarded as conservative because not all of the potential uncertainties are represented in the error bars. There are additional factors that might influence the $PM_{2.5}$ exposure trend but are not considered as major drivers (for example, land use and land cover changes, aerosol radiative feedbacks), which is a limitation of our study. However, the changes in $PM_{2.5}$ exposure and $PM_{2.5}$-related deaths induced by these factors are minor[22,64,65] compared with the factors considered in this study and will thus not influence our conclusions.

Data availability

The MEIC emission inventory is available from www.meicmodel.org. The dataset generated during this study is available in the figshare repository https://doi.org/10.6084/m9.figshare.14493375. Source data are provided with this paper.

Code availability

The code of the WRF model is available at https://www2.mmm.ucar.edu/wrf/users/download/get_sources.html. The code of the CMAQ model is available at https://github.com/USEPA/CMAQ/tree/5.0.1. The codes used for analysing data are available in the figshare repository https://doi.org/10.6084/m9.figshare.14493375.

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Author contributions
Q.Z. designed the research. Y.Z., G.G. and T.X. performed the research. H.Z., D.T., B.Z., M.L., F.L. and C.H. processed emission data. G.G., Y.Z., Q.Z., S.J.D. and K.H. interpreted data. G.G., Y.Z., Q.Z. and S.J.D. wrote the paper with input from all co-authors.

Competing interests
The authors declare no competing interests.

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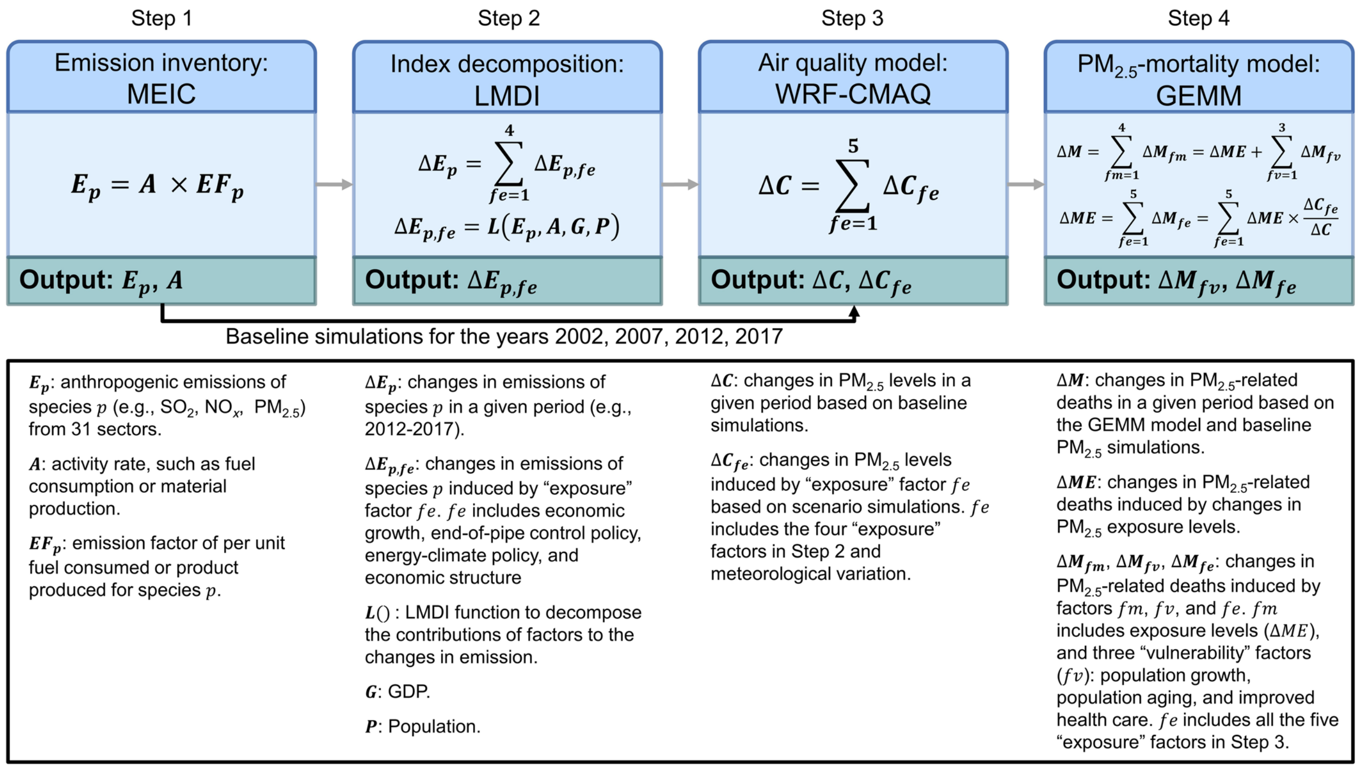
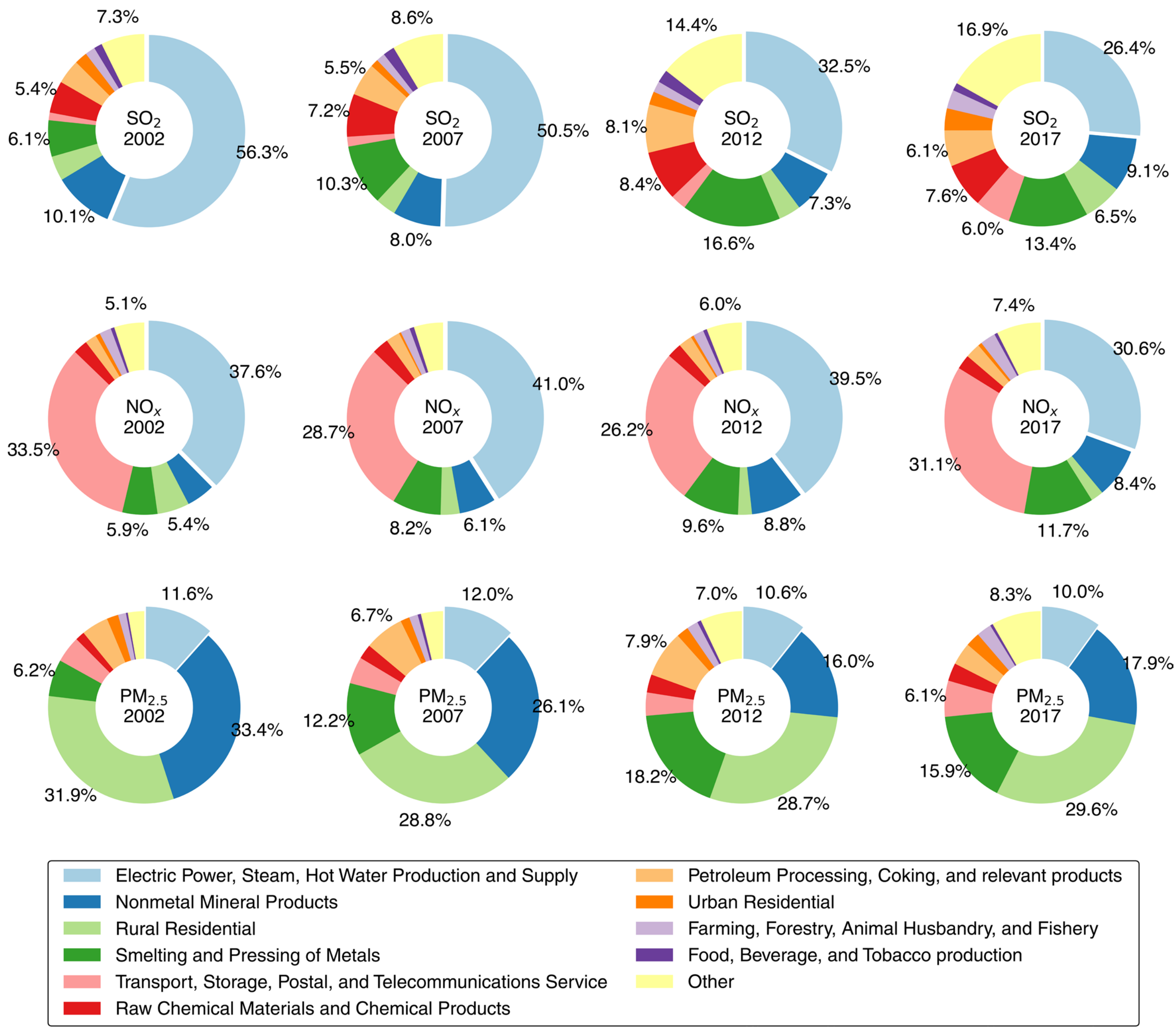
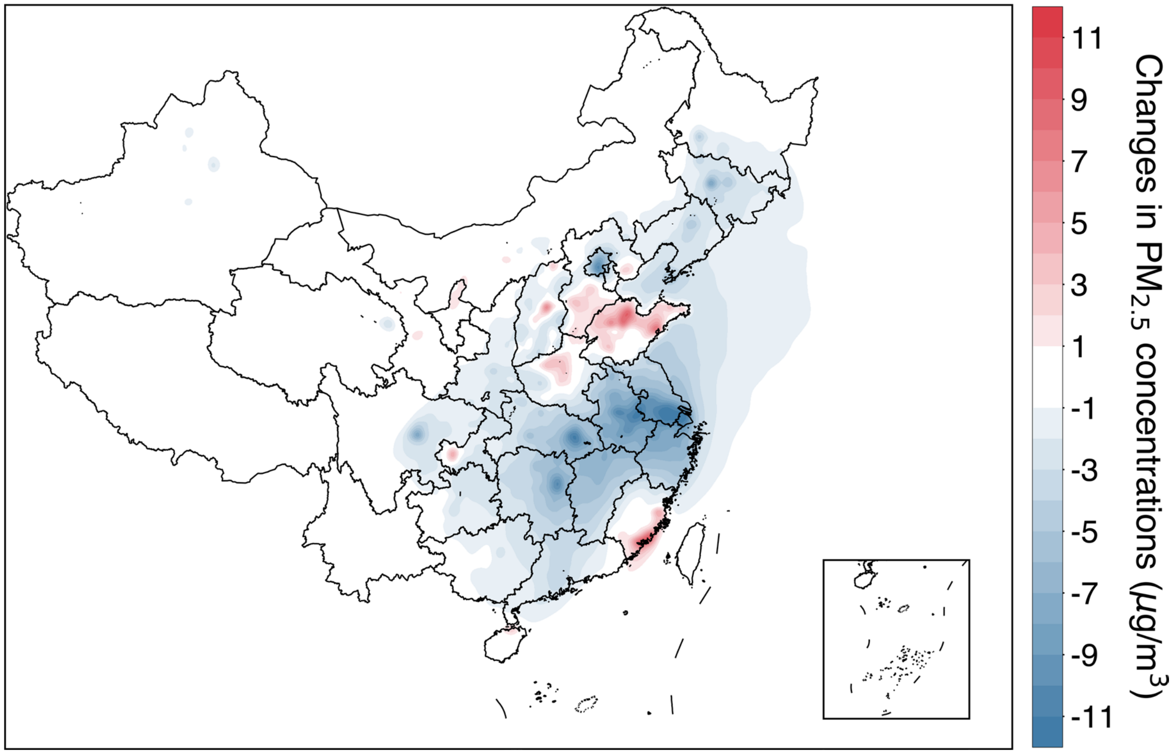


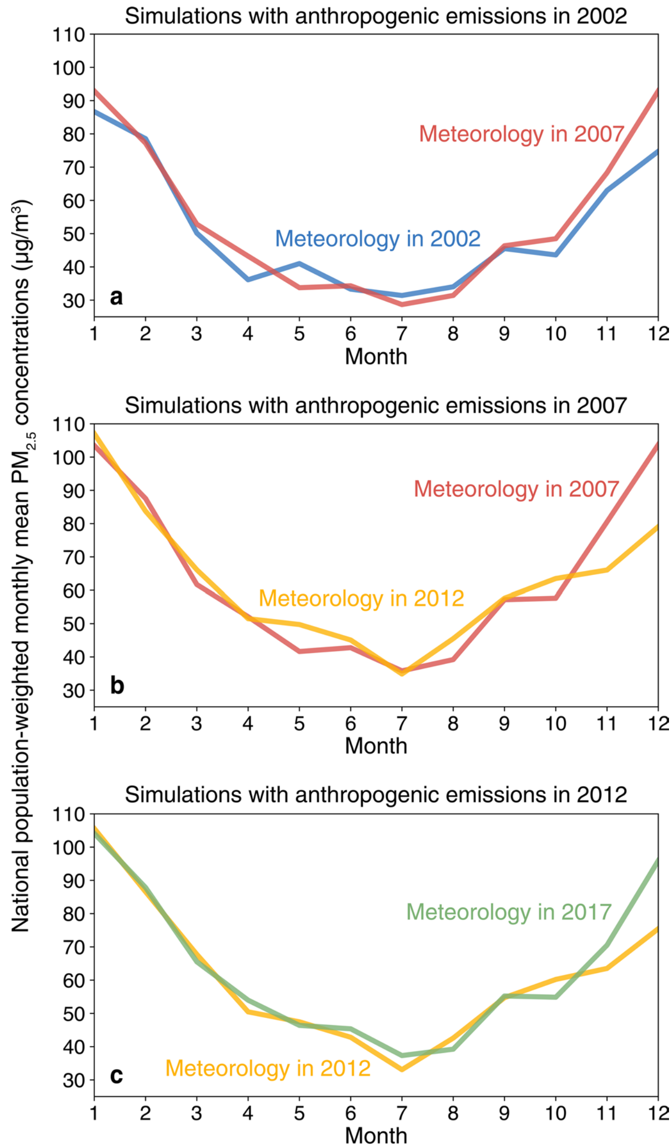
Extended Data Fig. 1 | Methodology framework to estimate drivers of China's $PM_{2.5}$-related deaths. The MEIC, LMDI, WRF, CMAQ, and GEMM represent the Multi-resolution Emission Inventory for China, the Logarithmic Mean Divisia Index decomposition analysis, the Weather Research and Forecasting Model, the Community Multiscale Air Quality Model, and the Global Exposure Mortality Model, respectively.



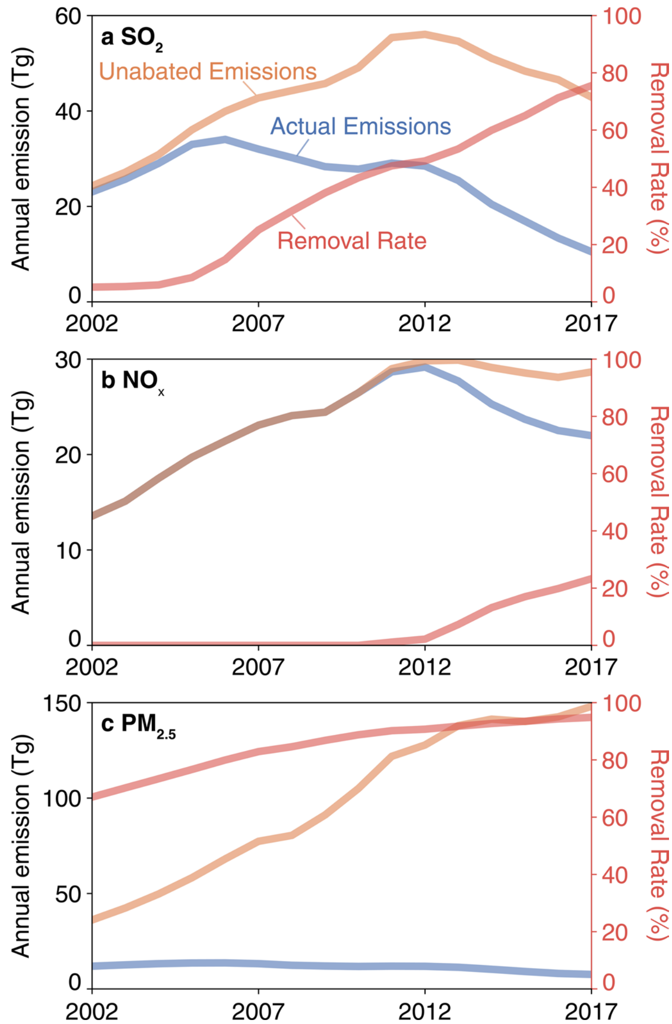
Extended Data Fig. 2 | Sectoral contributions of major air pollutant emissions in 2002–2017. Sectoral contributions of SO_2, NO_x, and primary $PM_{2.5}$ emissions for 11 sectors in 2002, 2007, 2012, and 2017.



Extended Data Fig. 3 | Changes in $PM_{2.5}$ concentrations associated with changes in economic structure in China from 2002 to 2007. Changes in economic structure majorly increased $PM_{2.5}$ concentrations over populated northern provinces such as Hebei, Shandong, and Henan, whose economy highly relies on heavy industries.



Extended Data Fig. 4 | Effects of interannual meteorological variations on the national population-weighted monthly mean $PM_{2.5}$ concentrations. Results for the sub-periods (**a**) 2002–2007, (**b**) 2007–2012, and (**c**) 2012–2017, respectively. These results are derived based on simulations of '*BASE*' and '*Fix emission*' scenarios.



Extended Data Fig. 5 | Trends in air pollutant emissions and emission removal rates in China over 2002–2017 for (a) SO_2, (b) NO_x, and (c) $PM_{2.5}$. The blue and orange lines represent actual and estimated unabated emissions, respectively. The red line represents average removal rates.

Extended Data Table 1 | Emission reduction measures implemented in China from 2002 to 2017

Period	Sector	Laws and regulations	Structural adjustment	PM removal measures	Desulfurization measures	Denitrification measures
2002–2007	Power	Revise emission standard for thermal power plants		Reinforce end-of-pipe control	Promote low-sulfur coal; promote end-of-pipe control (after 2006)	
	Industry	Revise emission standard for cement industry and industrial boilers	Promote precalciner kilns in cement industry	Reinforce end-of-pipe control	Promote low-sulfur coal	
	Transportation	Apply "China 1" and "China 2" emission standards				
	Residential					
2007–2012	Power		Optimize fleet mix (replace inefficient plants with efficient plants)	Promote high efficiency PM removal devices	Promote end-of-pipe control	Promote end-of-pipe control
	Industry		Phase out outdated capacities and technologies	Promote high efficiency PM removal devices in cement industry	Promote end-of-pipe control for heating	
	Transportation	Apply "China 3" emission standard				
	Residential				Promote low-sulfur coal	
2012–2017	All	Revise "Law on the Prevention and Control of Atmospheric Pollution" and "Ambient air quality standards"				
	Power	Strengthen emission standard for thermal power plants	Optimize fleet mix; promote non-fossil fuel	Upgrade control devices to meet "ultralow emission" standard	Upgrade control devices to meet "ultralow emission" standard	Upgrade control devices to meet "ultralow emission" standard
	Industry	Strengthen emission standards for all emission-intensive industries	Phase out outdated capacities and technologies	Promote high efficiency PM removal devices in cement industry; Reinforce control for industrial kilns and boilers	Promote end-of-pipe control for heating, and iron and steel industries	Promote end-of-pipe control for heating, and cement industries
	Transportation	Apply "China 4" and "China 5" emission standards	Upgrade fuel quality; eliminate old and "yellow-label" vehicles			
	Residential		Promote clean coal; substitute coal by electricity and natural gas; promote clean stove	Upgrade end-of-pipe control for residential boilers	Promote end-of-pipe control for residential boilers	

Note: PM refers to particle matters

Extended Data Table 2 | Variations in NO_x emissions in major sectors and the changes induced by end-of-pipe control policies during 2002–2017 (unit: Tg)

	2002 emission	Total emission changes			Effects of end-of-pipe control policies		
		2002–2007	2007–2012	2012–2017	2002–2007	2007–2012	2012–2017
Total	13.5	9.5	6.1	–7.2	–0.7	–2.0	–7.7
Electric Power, Steam and Hot Water Production and Supply	5.1	4.4	2.1	–4.8	–0.5	–1.4	–5.5
Transport, Storage, Postal, and Telecommunications Service	4.5	2.1	1.0	–0.8	–0.7	–1.2	–1.3
Smelting and Pressing of Metals	0.8	1.1	0.9	–0.2	0.0	–0.1	0.1
Nonmetal Mineral Products	0.6	0.8	1.1	–0.7	0.5	0.7	–0.9

Extended Data Table 3 | Sensitivity tests of national population-weighted annual mean $PM_{2.5}$ concentrations

	$PM_{2.5}$ concentration in 2002	$PM_{2.5}$ concentration in 2007	$PM_{2.5}$ concentration in 2012	$PM_{2.5}$ concentration in 2017
Population distribution in 2002	51.51	63.46	60.95	42.22
Population distribution in 2007	51.75	63.61	60.90	42.19
Population distribution in 2012	52.03	63.78	60.86	42.17
Population distribution in 2012	52.33	63.98	60.83	42.15

National population-weighted annual mean $PM_{2.5}$ concentrations calculated based on combinations of $PM_{2.5}$ concentration and population distribution from different years (unit: μg m^{-3}).