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Air quality co-benefits of carbon pricing in China

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Climate policies targeting energy-related CO_2 emissions, which act on a global scale over long time horizons, can result in localized, near-term reductions in both air pollution and adverse human health impacts. Focusing on China, the largest energy-using and CO_2-emitting nation, we develop a cross-scale modelling approach to quantify these air quality co-benefits, and compare them to the economic costs of climate policy. We simulate the effects of an illustrative climate policy, a price on CO_2 emissions. In a policy scenario consistent with China's recent pledge to reach a peak in CO_2 emissions by 2030, we project that national health co-benefits from improved air quality would partially or fully offset policy costs depending on chosen health valuation. Net health co-benefits are found to rise with increasing policy stringency.

Advancing environmental sustainability in systems with multiple interacting natural and human components is a major scientific and analytical challenge. Climate change and local air quality are two threats to sustainability that offer significant potential for co-control[1–4], because emissions of CO_2, the major energy-linked greenhouse gas (GHG), originate from many of the same combustion processes responsible for emissions of air pollutants. Efforts to identify co-control opportunities are complicated by the difficulty of simulating how policy acts across space and time and interacts with complex, and often nonlinear, relationships among economic activity, emissions, ambient air quality and human health.

Addressing climate change will require deep cuts in global emissions of CO_2 and other GHGs. Many developing nations, including China, have pledged to control domestic GHG emissions under the 2015 Paris Agreement[5]. These efforts interact with a broader set of non-target sustainability challenges[6], among them air quality. Degraded air quality is an immediate, often localized environmental burden and a leading cause of mortality[7]. Here we focus on these interactions in China. China's high coal share makes it the world's leading GHG emitter and home to severe local pollution. While climate policy does not necessarily trigger the most cost-effective air pollution control strategies, co-benefits form an important basis for coordinating air quality and climate policy when the latter is binding.

Among climate change policy studies, several have focused on co-benefits[4,8]. Co-benefits are outcomes not directly targeted by policy, including reductions in non-targeted pollutants[9], changes in air quality[10], reduced adverse health outcomes[2] and avoided economic costs[11]. In the United States, Thompson et al.[10] found large but rapidly diminishing co-benefits with increasing climate policy stringency. Shindell et al.[12] showed that CO_2 reductions in the United States that are consistent with a 2 °C global target would deliver near-term benefits that would probably exceed policy costs.

Co-benefits studies for China have largely focused on the impacts of climate or air pollution policies on national and, in a few cases, provincial emissions. In a model that captures pollution abatement costs, Nam et al.[13] evaluated the SO_2 reduction target in China's Eleventh Five Year Plan (2006–2010), and found that non-target reductions in CO_2 exceeded the stringency of a concurrent carbon intensity target. Dong et al.[9] used a provincial economic model of China to predict energy consumption, and applied an optimization tool to select cost-effective end-of-pipe technologies and estimate CO_2 and air pollution emissions in 2030. They found that well-developed regions see only marginal co-benefits in terms of reduced air pollutant emissions, while provinces that are large energy users or are relatively coal- or industry-intensive obtain larger co-benefits[9].

A few China-focused studies have extended policy assessment to air quality, but either omitted or presented only aggregated national health effects, and did not consider how policy dynamically shapes the evolution of the energy system. He et al.[14] quantified the impact of energy policies in China on air pollution, taking as an input sustainable energy scenarios described in government plans[15], and focusing on formation of fine particulate matter with a diameter less than or equal to 2.5 μm ($PM_{2.5}$). Nielsen and Ho[11] simulated the impact of national air pollution policy on energy use, emissions, air quality and public health in a single-region model of China, showing that SO_2 controls during the Eleventh Five-Year Plan (2006–2010) delivered significant public health benefits, while a nationwide CO_2 tax was projected to improve air quality at low cost.

We establish a novel, cross-scale integrated approach to assess co-benefits and costs that captures how policy alters the economy and energy system across spatial scales (here, provincial to national), time horizons (our dynamic energy–economic model captures evolution of the energy system from 2010 to 2030) and as a function of policy ambition. Our analysis captures the contribution of airborne pollution transport, simulating nonlinear relationships among emissions, air quality and health effects, while preserving regional detail, in a self-consistent framework. This integrated co-benefits analysis of a developing country (China) resolves sub-national spatial as well as temporal impacts of policy.

To simulate policy impacts and economy–environment interactions, we develop the regional emissions air quality climate and health (REACH) framework, which couples an energy–economic model, the China Regional Energy Model (C-REM), with an atmospheric

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chemistry model, GEOS-Chem. C-REM is a global general equilibrium model that resolves China's economy and energy system at the provincial level, including production, consumption, interprovincial and international trade, energy use and emissions of CO_2 and local pollutants[16,17]. C-REM has been previously used to model China's interlinked energy and economic system at the provincial level[18–20]. Using C-REM, we first simulate a CO_2 price, which results in deployment of least-cost CO_2 reduction strategies to meet a CO_2 intensity constraint, and obtain provincial energy use and emissions of CO_2 and air pollutants through to 2030. We model three policy scenarios that target CO_2 intensity reductions of 3%, 4% or 5% per year between 2015 and 2030 (3% Policy, 4% Policy and 5% Policy), and compare them to a No Policy scenario. The 3% Policy simulates a continuation of China's CO_2 intensity reduction commitment prior to the 2015 Paris Agreement; total CO_2 emissions in 2030 are projected to be 13.5 gigatons (Gt). The 4% Policy is consistent with China's recent commitment to halt its rise in CO_2 emissions by 2030 (with projected CO_2 emissions of 11.4 Gt in 2030), achieving a 60–65% reduction in CO_2 intensity by 2030 relative to its 2005 level. The 5% Policy reduces China's CO_2 intensity to the projected world average in 2030 (with projected emissions of 9.7 Gt in 2030), and is comparable to the scenario described by Raftery et al.[21], which limits the global temperature increase to 2 °C. Emissions factors for each pollutant by province, sector and energy type in 2007 are derived from emissions reported in the Regional Emission Inventory in Asia (REAS)[22], and are calibrated to 2010 and 2015 based on national total emissions reported in the multi-resolution emission inventory for China (MEIC)[23]. To obtain anthropogenic emissions of air pollutants and their precursors in 2030 for each scenario, levels of economic activity or energy use simulated in C-REM are used to scale associated sectoral emissions in 2015 assuming an exponential decay in emissions factors through to 2030 to account for the technology improvement in end-of-pipe controls. These emissions are then input to GEOS-Chem (v. 9-01-03, with a horizontal resolution of 0.5° × 0.667° in East Asia) to simulate $PM_{2.5}$ formation. We then calculate national and provincial monetized health damages from $PM_{2.5}$ using three concentration–response functions and two health valuation methods to examine uncertainties in health co-benefits. Further information is provided in Methods.

Results

At the national level, the 4% Policy scenario leads to a 24% reduction in CO_2 emissions in 2030, relative to the No Policy case. The CO_2 price required to achieve these reductions rises to US\$72 ton^{-1} in 2030 (CO_2 prices are reported in 2007 US\$). Most of the CO_2 reduction in 2030 is a result of a 20% energy intensity reduction (relative to the No Policy scenario in 2030), reflecting the combined effect of higher energy efficiency and sectoral composition change. Coal is substantially affected. Under the 4% Policy, coal represents 54% of total energy use in 2030, down from 69% in 2010, while substitution by clean energy contributes only modestly (see Fig. 1a). Figure 1b–d shows sectoral reductions in energy use and emissions under the 4% Policy. The energy-intensive and manufacturing industries sector, which includes iron and steel, non-ferrous metals, non-metallic materials and chemicals, experiences the largest reduction in energy use and emissions of CO_2 and air pollutants. The electricity sector, which consumes primarily coal, experiences the second largest reduction. Oil use in transportation is less affected: it has a lower CO_2 emissions factor compared to coal, and has few cost-effective substitutes. As policy stringency increases, the CO_2 price increases from US\$26 ton^{-1} with a 3% Policy to US\$132 ton^{-1} with a 5% Policy in 2030. Emissions of CO_2 in the 4% Policy case are projected to peak in 2025 at 11.5 Gt, and are estimated to peak in 2020 at 10.6 Gt under the 5% Policy. Emissions trajectories are shown for all cases in Fig. 2a.

Regionally, simulated changes in consumption, energy use and CO_2 emissions under the 4% Policy compared to the No Policy scenario vary widely across China's provinces (Supplementary Fig. 3). Substantial CO_2 emissions reductions in both relative and absolute terms occur in Shanxi, Guizhou and Inner Mongolia (by 51%, 43% and 35%, respectively), largely in the mining and energy-intensive manufacturing sectors, reflecting abundant low-cost opportunities to improve coal use efficiency in provinces with a large share of energy-intensive industry and high energy intensity. Economic impacts in terms of changes in consumption are also larger in these provinces because their coal production accounts for a large share of provincial GDP. Importantly, the provincial distribution of policy costs depends on the initial allocation of emissions allowances[20]. In our policy simulation, CO_2 emissions allowances are initially distributed according to 2010 emissions and increased over time in proportion to provincial GDP. Projected co-benefits could provide a basis for adjusting this allocation across provinces to limit uneven impacts.

National-level impacts of climate policy on pollutant reductions vary widely. We focus on sulfur dioxide (SO_2), nitrogen oxides (NO_x) and ammonia (NH_3), which combine in the atmosphere to form inorganic $PM_{2.5}$, as well as black carbon (BC) and primary organic carbon (OC) (see Fig. 2b–f). Climate policies lead to the largest reductions in SO_2 and NO_x because these emissions are closely associated with coal combustion, the energy type most impacted by policy. Under the 4% Policy, we find a 25% reduction in SO_2 and a 19% reduction in NO_x in 2030 relative to the No Policy scenario. Climate policies have a limited effect on NH_3 because >80% of NH_3 is emitted from the agricultural sector.

The No Policy scenario in 2030 has a national population-weighted annual average $PM_{2.5}$ concentration of 70.1 μg m^{-3}. Relative to No Policy levels in 2030, $PM_{2.5}$ concentration falls by 4.7% under the 3% Policy, 12% under the 4% Policy and 19% under the 5% Policy (these levels represent an increase of 21%, 12% and 3.5% relative to 2010, respectively; see Fig. 3). Modest changes in national population-weighted $PM_{2.5}$ mask large variation in provincial impacts. Comparing Fig. 3a,b, air quality in central China degrades more than in other regions, as projected economic growth rates, reflected in government plans, are higher. Climate policies therefore deliver larger air quality benefits in this region (Fig. 3c–e). Coal consumption centres, including Shanxi and Guizhou, experience greater air quality improvements than other provinces, with population-weighted $PM_{2.5}$ reduced by 17%. By contrast, the most populated eastern regions experience less improvement. Larger shares of light industry and services in these economies limit CO_2 reduction opportunities from more energy-intensive sectors. These economies also have higher pre-existing energy efficiency, making incremental CO_2 reductions relatively costly. Under the 4% Policy, population-weighted $PM_{2.5}$ decreases by 14–15% in urban Beijing, Tianjin and Hebei, and decreases 10–11% in coastal Jiangsu, Zhejiang, Fujian and Guangdong, relative to 2030 levels in the No Policy scenario (Supplementary Fig. 3).

At the national level in 2030, total premature mortalities in the No Policy scenario total >2.3 million, and projected $PM_{2.5}$ reductions result in ~36,000, 94,000 and 160,000 avoided premature mortalities in the 3% Policy, 4% Policy and 5% Policy scenarios, respectively, using exposure–response relationships from the Global Burden of Disease (GBD) study[24]. Estimated avoided premature deaths in 2030 under the 4% Policy scenario are more than an order of magnitude higher than those estimated for the US Clean Power Plan in 2030[25]. Avoided mortalities using alternative exposure–response relationships are provided in Supplementary Table 5. Health co-benefits in the 4% Policy scenario are 3.7 times larger than policy costs if international estimates are used for health valuation, while co-benefits offset 26% of policy costs using recent Chinese estimates (see discussion in Methods). Monetized values of health co-benefits (before considering policy cost) vary widely across provinces, from US\$1.6 billion in Ningxia to US\$53.7 billion in Guangdong in the 4% Policy scenario (Supplementary Table 5).

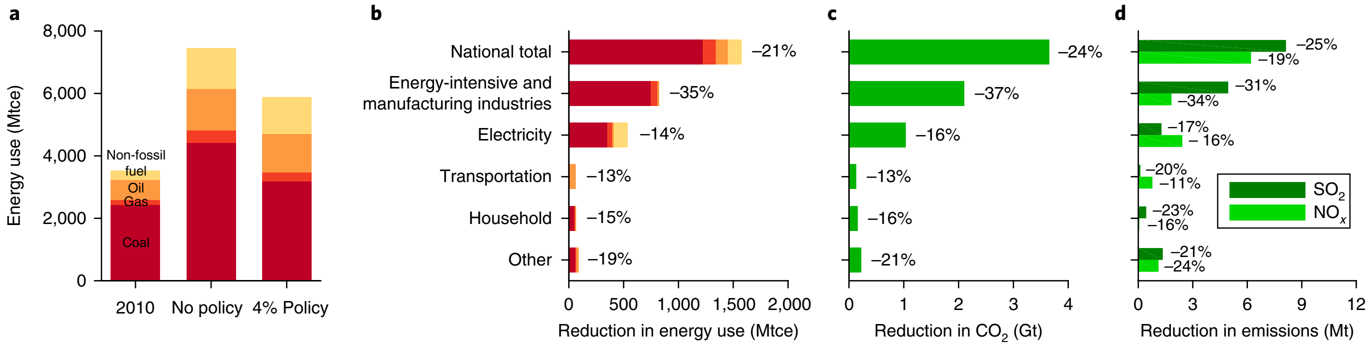

Fig. 1 | Changes in energy use and emissions in the 4% Policy scenario compared to the No Policy scenario in 2030. a,**b**, Changes in energy use at the national (**a**) and sectoral (**b**) levels. Mtce, million tons of coal equivalent. **c**,**d**, Sectoral reductions in CO_2 (**c**) and SO_2 and NO_x (**d**) emissions (with percentage changes to the right of each bar) in the 4% Policy scenario compared to the No Policy scenario in 2030.

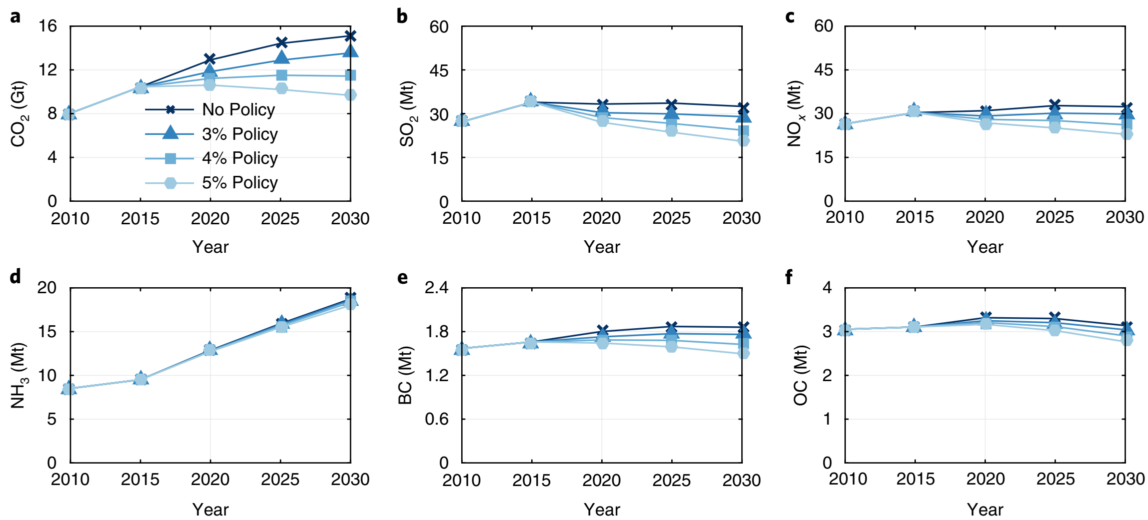

Fig. 2 | Impacts of changing policy stringency on emissions of CO_2 and air pollutants. a–**f**, Simulated CO_2 (**a**) and pollutant emissions (**b**–**f**) under the No Policy scenario and Policy scenarios targeting annual CO_2 intensity reductions ranging from 3% to 5%. The legend in **a** applies to all panels.

Discussion

The set of relationships affecting health co-benefits from climate policy in each province, denoted by subscript i, is captured by the relationship in equation (1). Each ratio in equation (1) is governed by nonlinear, interacting processes. The monetary value of health co-benefits changes (in percentage terms) ΔHCB_i due to policy is affected by associated changes in mortality (ΔM_i), relationships between mortality and $PM_{2.5}$ changes, $\Delta PM_{2.5,i}$, the concentration–response relationship, $PM_{2.5}$ reductions delivered as a result of CO_2 emissions reduction ($\Delta CO_{2,i}$), and CO_2 emissions reduction associated with changes in energy use (ΔE_i). At the national level, these relationships are illustrated in Fig. 4a for varying policy stringency, and in Fig. 4c by province for the 4% Policy scenario. The relationship between economic cost and avoided health damages by province is shown in Fig. 4b.

$$\Delta HCB_i = \frac{\Delta HCB_i}{\Delta M_i} \times \frac{\Delta M_i}{\Delta PM_{2.5,i}} \times \frac{\Delta PM_{2.5,i}}{\Delta CO_{2,i}} \times \frac{\Delta CO_{2,i}}{\Delta E_i} \times \Delta E_i \quad (1)$$

$$\frac{\Delta PM_{2.5,i}}{\Delta CO_{2,i}} = \frac{\Delta PM_{2.5,i}}{\Delta precursors_i} \times \frac{\Delta precursors_i}{\Delta CO_{2,i}} \quad (2)$$

As shown in Fig. 4a, the relative reduction of population-weighted $PM_{2.5}$ at the national level in each scenario is less than proportional to the associated CO_2 reduction. Equation (2) captures a critical step that explains this. $\frac{\Delta PM_{2.5,i}}{\Delta CO_{2,i}}$ depends on relative changes in the inorganic precursors that combine to form $PM_{2.5}$: SO_2, NO_x and NH_3. Complexes of ammonium nitrate and ammonium sulfate are important components of $PM_{2.5}$. Climate policy reduces SO_2 proportionally more than NH_3, because the former is co-emitted with CO_2 from power plants and industrial facilities, while the latter is primarily emitted from agricultural sources. NO_x is reduced proportionally less than SO_2 because NO_x is emitted from vehicles as well as power plants, and vehicles are less impacted by the policy. Thus, as policy stringency increases, SO_2 falls most, NO_x falls moderately and NH_3 falls least, with this ratio varying across provinces. Although the relative sulfate reduction is nearly proportional to CO_2 reduction, the relative nitrate reduction is much lower. Co-benefits from the reduction of sulfate–nitrate–ammonium aerosols account for 87% of total $PM_{2.5}$ co-benefits. The contribution from BC and primary OC is lower because their emissions are mostly from biomass burning, which is not directly affected by a climate policy that targets CO_2. Secondary organic aerosols are not included in this analysis as their main precursors (volatile organic compounds) are only slightly targeted by the policy (2–10%), and secondary organic

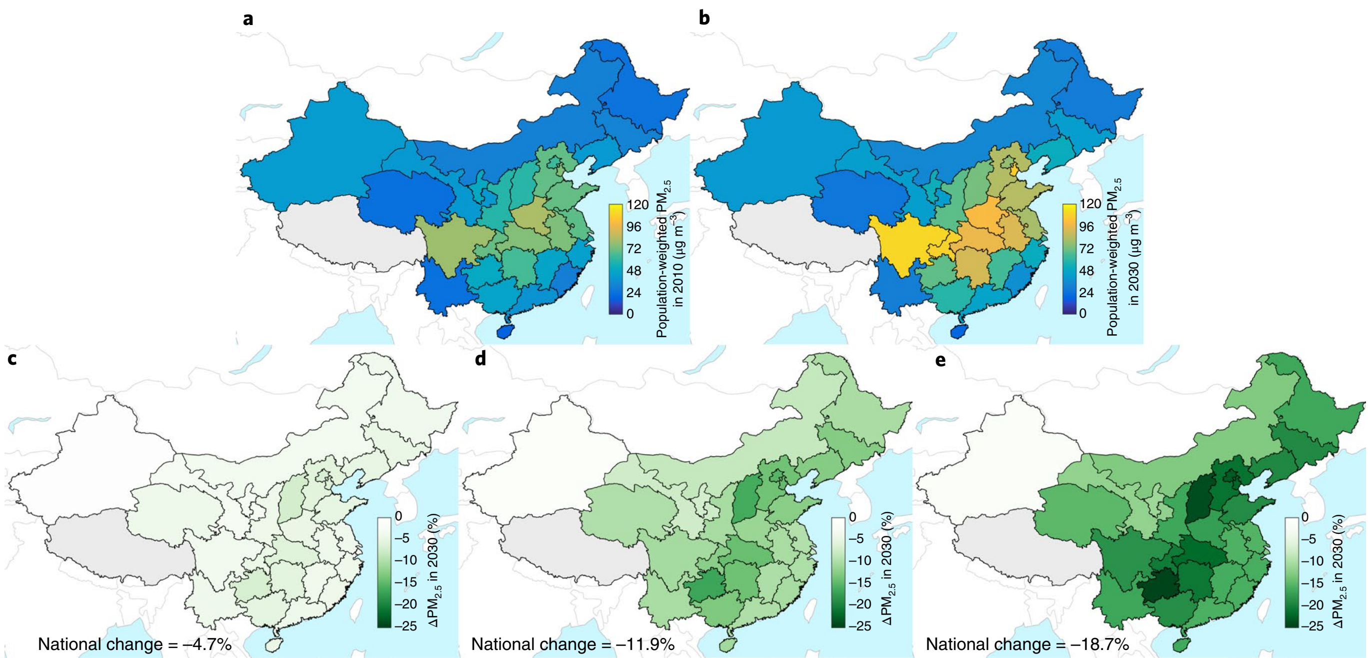

Fig. 3 | Spatial distribution of population-weighted $PM_{2.5}$. a,**b**, The annual average of population-weighted $PM_{2.5}$ concentrations in 2010 (**a**) and under the No Policy scenario in 2030 (**b**). **c**–**e**, Difference in 2030 population-weighted $PM_{2.5}$ concentrations between the Policy scenarios (3%, 4% and 5%) and the No Policy scenario.

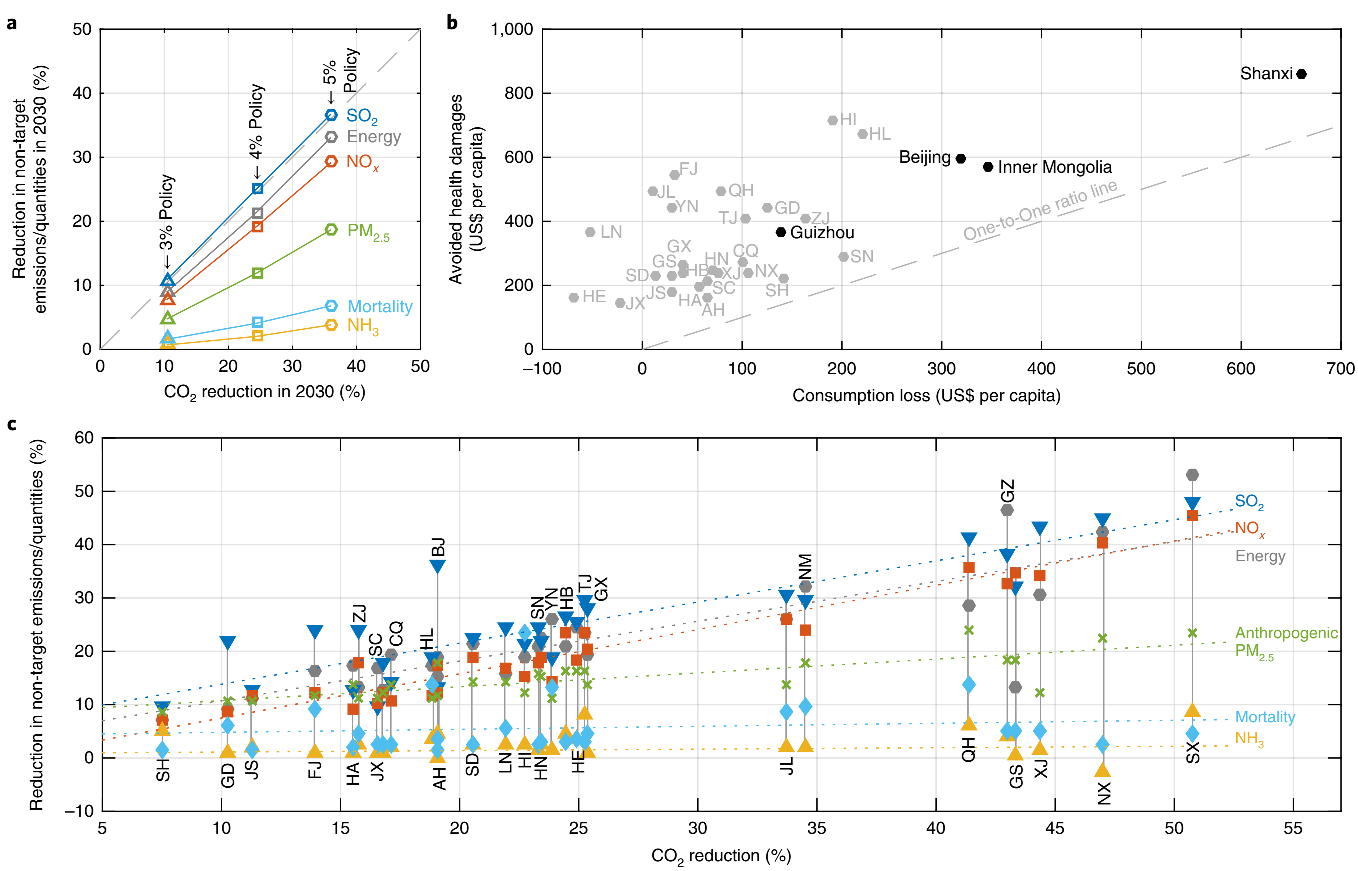

Fig. 4 | Air quality co-benefits of climate policy. a, Reduction in non-target pollutants/quantities under different national-level policy stringencies, **b**, Provincial distribution of policy costs and avoided health damages per capita in 2030 under the 4% Policy (Province name abbreviations are listed in Supplementary Table 1). **c**, Provincial distribution of reductions in non-target pollutants/quantities in 2030 under the 4% Policy (dotted lines denote linear trends for each pollutant/quantity). Detailed provincial results are presented in Supplementary Figs. 3 and 4.

aerosols only account for about 5% of Chinese annual mean $PM_{2.5}$ in GEOS-Chem (for example, see Fu et al.[26]). Moreover, GEOS-Chem resolves major Chinese urban centres in 6–8 grid boxes, which may dilute localized poor air quality, affecting projected health effects. For the United States, however, Thompson et al.[10] found that calculated benefits were robust to the resolution selected.

To illustrate the influence of chemical interactions, and because NH_3 projections are uncertain, we conduct GEOS-Chem simulations with NH_3 emissions constant at 2010 levels, around 46% of that in the No Policy scenario in 2030. Results show that limiting the NH_3 increase results in a further 12.3% reduction in population-weighted $PM_{2.5}$ under the 4% Policy scenario. Co-benefits in $PM_{2.5}$ concentrations under the 4% Policy fall from 12% to 9.7% if NH_3 emissions are kept at 2010 levels because of reduced co-benefits from nitrate. This exercise illustrates the importance of accounting for and controlling NH_3 as a complementary and even synergistic measure alongside climate policy, as suggested by earlier studies[27,28].

The relationship between changes in CO_2 and anthropogenic $PM_{2.5}$ at the provincial level is shown in Fig. 4c. Although SO_2 and NO_x emissions are reduced nearly in proportion to CO_2 emissions, the reduction in anthropogenic $PM_{2.5}$ is smaller, mainly because of the relatively small change in NH_3 emissions and the limited availability of SO_2 and NO_x oxidants. In addition, we find variation in this relationship across provinces, which reflects regional variations in the composition of the energy system and abatement costs, pollutants and resulting chemistry, and transport of air pollutants from neighbouring provinces. For example, Beijing, the national capital and a populous urban centre with limited coal-intensive industry, reduces CO_2 emissions and anthropogenic $PM_{2.5}$ by 19% and 18% respectively under the 4% Policy scenario. This relatively large reduction in anthropogenic $PM_{2.5}$ follows from the fact that the least-cost CO_2 abatement opportunities pursued under the policy also reduce SO_2 emissions from its few remaining sources. As a result, Beijing has larger net benefits per capita (Fig. 4b). By contrast, the reduction in anthropogenic $PM_{2.5}$ in Shanxi is only 23% despite reducing CO_2 emissions by 51%. This nonlinearity is largely due to local atmospheric chemistry: a limited decrease in nitrate concentration in response to the 45% decline of NO_x emissions. Considering total $PM_{2.5}$, including contributions from non-anthropogenic sources such as dust, relative changes correlate even less with CO_2 reductions (see Supplementary Fig. 5 for provincial results comparing anthropogenic and total $PM_{2.5}$).

At the national level, avoided mortality rises as policy stringency increases, as shown in Fig. 4a, but its relative increase is lower than for $PM_{2.5}$. Nevertheless, avoided mortality translates into net health co-benefits that rise faster than policy costs. Net co-benefits based on an international value of statistical life (VSL) approach are projected to be US\$138.4 billion in the 3% Policy scenario (US\$173.1 billion in health co-benefits minus US\$34.7 billion in costs), US\$339.6 billion in the 4% Policy scenario (US\$464.5 billion in health co-benefits minus US\$125.0 billion in costs) and US\$534.8 billion in the 5% Policy scenario (US\$790.7 billion minus US\$255.9 billion). Coal represents a large initial share of the energy mix, and remains the marginal fuel reduced by climate policy over the range of policy stringency considered. Reducing coal use, which continues with increasing policy stringency, brings large reductions in co-emitted pollutants.

Our framework could readily be extended to study the impact of other policies and technologies on a wide range of sustainability outcomes. For instance, it could be used to consider the air quality co-benefits of other climate policies (such as renewable energy subsidies) or to study the climate co-benefits of air quality policies, which would require augmenting the model with the costs of air pollution control technologies. Our framework could further be extended to capture other unintended consequences of policy, such as impacts on agriculture and water supplies, allowing for more holistic analysis of sustainability impacts.

Implications for climate and sustainability policy. Air quality improvement is a valuable co-benefit of carbon pricing that increases with policy stringency in China. Even without considering the social cost of carbon[29], a measure of direct benefits of climate policy per ton of CO_2 abated, health co-benefits can outweigh policy costs to households. This is relevant for other developing nations, especially those that rely on coal with limited end-of-pipe pollution control. As China has formally announced plans to introduce a national emissions trading system, our results suggest that such a system covering many energy-intensive sectors could have large aggregate benefits, providing a powerful incentive for adoption, but uneven local impacts. Our results show that even a modest CO_2 price would yield substantial net health co-benefits, while tightening policy over the range considered here would increase them. We also note that the CO_2 price itself will not achieve Chinese ambient air quality standards[30] with an annual average limit of $35\,\mu g\,m^{-3}$ in 2030; further end-of-pipe control and reduction of pollution from non-combustion sources, such as NH_3, will be needed. Our framework further reveals the difficulties associated with balancing coverage of a large area to maximize cost-effective abatement against the recognition that concomitant air quality improvements will not always occur where potential health benefits are greatest. Policymakers should therefore consider how carbon policy and air quality control policy interact when formulating new proposals.

Methods

Methods, including statements of data availability and any associated accession codes and references, are available at https://doi.org/10.1038/s41593-017.

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References

1. Aunan, K., Fang, J., Vennemo, H., Oye, K. & Seip, H. M. Co-benefits of climate policy—lessons learned from a study in Shanxi, China. *Energy Policy* **32**, 567–581 (2004).
2. Shindell, D. et al. Simultaneously mitigating near-term climate change and improving human health and food security. *Science* **335**, 183–189 (2012).
3. McCollum, D. L. et al. Climate policies can help resolve energy security and air pollution challenges. *Climatic Change* **119**, 479–494 (2013).
4. West, J. J. et al. Co-benefits of global greenhouse gas mitigation for future air quality and human health. *Nat. Clim. Change* **3**, 885–889 (2013).
5. *China's Intended Nationally Defined Contribution (INDC): Enhanced Actions on Climate Change* (Department of Climate Change, National Development and Reform Commission, 2015).
6. Nemet, G. F., Holloway, T. & Meier, P. Implications of incorporating air-quality co-benefits into climate change policymaking. *Environ. Res. Lett.* **5**, 14007 (2010).
7. Vos, T. et al. Global, regional, and national incidence, prevalence, and years lived with disability for 301 acute and chronic diseases and injuries in 188 countries, 1990–2013: a systematic analysis for the Global Burden of Disease Study 2013. *Lancet* **386**, 743–800 (2015).
8. Parry, I., Veung, C. & Heine, D. How much carbon pricing is in countries' own interests? The critical role of co-benefits. *Clim. Change Econ.* **6**, 1550019 (2015).
9. Dong, H. et al. Pursuing air pollutant co-benefits of CO_2 mitigation in China: a provincial leveled analysis. *Appl. Energ.* **144**, 165–174 (2015).
10. Thompson, T. M., Rausch, S., Saari, R. K. & Selin, N. E. A systems approach to evaluating the air quality co-benefits of US carbon policies. *Nat. Clim. Change* **4**, 917–923 (2014).
11. Nielsen, C. P. & Ho, M. S. *Clearer Skies Over China* (MIT Press, Cambridge, 2013).
12. Shindell, D. T., Lee, Y. & Faluvegi, G. Climate and health impacts of US emissions reductions consistent with 2 °C. *Nat. Clim. Change* **6**, 503–507 (2016).
13. Nam, K. M., Waugh, C. J., Paltsev, S., Reilly, J. M. & Karplus, V. J. Carbon co-benefits of tighter SO_2 and NO_x regulations in China. *Glob. Environ. Change* **23**, 1648–1661 (2013).
14. He, K. et al. Co-benefits from energy policies in China. *Energy* **35**, 4265–4272 (2010).
15. Zhou, D. *China Sustainable Energy Scenarios in 2020* (China Environmental Science Press, 2003).

16. Zhang, D., Rausch, S., Karplus, V. J. & Zhang, X. Quantifying regional economic impacts of CO_2 intensity targets in China. *Energy Econ.* **40**, 687–701 (2013).
17. Luo, X., Caron, J., Zhang, D., Zhang, X. & Karplus, V. J. Interprovincial migration and the stringency of energy policy in China. *Energy Econ.* **58**, 164–173 (2016).
18. Springmann, M., Zhang, D. & Karplus, V. J. Consumption-based adjustment of emissions-intensity targets: an economic analysis for China's provinces. *Environ. Resour. Econ.* **61**, 615–640 (2015).
19. Karplus, V. J., Rausch, S. & Zhang, D. Energy caps: Alternative climate policy instruments for China? *Energ. Econ.* **56**, 422–431 (2016).
20. Zhang, D., Springmann, M. & Karplus, V. J. Equity and emissions trading in China. *Climatic Change* **134**, 131–146 (2016).
21. Raftery, A. E., Zimmer, A., Frierson, D. M. W., Startz, R. & Liu, P. Less than 2 °C warming by 2100 unlikely. *Nat. Clim. Change* **7**, 637–641 (2017).
22. Kurokawa, J. et al. Emissions of air pollutants and greenhouse gases over Asian regions during 2000–2008: Regional Emission inventory in ASia (REAS) version 2. *Atmos. Chem. Phys.* **13**, 11019–11058 (2013).
23. *MEIC* v1.2 (MEIC Research Group, Tsinghua University, 2015); http://www.meicmodel.org/dataset-meic.html
24. Burnett, R. T. et al. An integrated risk function for estimating the global burden of disease attributable to ambient fine particulate matter exposure. *Environ. Health Perspect.* **122**, 397–403 (2014).
25. Driscoll, T. C. et al. US power plant carbon standards and clean air and health co-benefits. *Nat. Clim. Change* **5**, 535–540 (2015).
26. Fu, T. M. et al. Carbonaceous aerosols in China: top-down constraints on primary sources and estimation of secondary contribution. *Atmos. Chem. Phys.* **12**, 2725–2746 (2012).
27. Wang, S. et al. Impact assessment of ammonia emissions on inorganic aerosols in East China using response surface modeling technique. *Environ. Sci. Technol.* **45**, 9293–9300 (2011).
28. Wang, Y., Zhang, Q. Q., He, K., Zhang, Q. & Chai, L. Sulfate-nitrate-ammonium aerosols over China: response to 2000–2015 emission changes of sulfur dioxide, nitrogen oxides, and ammonia. *Atmos. Chem. Phys.* **13**, 2635–2652 (2013).
29. Tol, R. S. J. The social cost of carbon. *Annu. Rev. Resour. Econ.* **3**, 419–443 (2011).
30. *Ambient Air Quality Standards* GB 3095–2012(China MEP, 2012); http://english.mep.gov.cn/Resources/standards/Air_Environment/quality_standard1/201605/W020160511506615956495.pdf

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Author contributions

V.J.K. and N.E.S. conceived the research. M.L. and C.-T.L. performed the modeling simulations. M.L., C.-T.L., K.M.M. and D.Z. analysed data. D.Z. developed the China Regional Energy Model (C-REM). All authors wrote the paper.

Competing interests

The authors declare no competing interests.

Additional information

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Methods

C-REM. C-REM is a global general equilibrium model that resolves China's economy and energy system at the provincial level, including production, consumption, interprovincial and international trade, energy use and emissions of CO_2 and local pollutants. Several previous analyses have used C-REM to evaluate China's energy and climate policy[18–20]. The model represents 30 provinces in mainland China in detail and divides the rest of the world into four regions (United States, Europe, other developing countries and other developed countries). In China, the model represents production, intermediate input flows, consumption, interprovincial trade and energy based on China's Regional Input–Output Tables[31] (for 2007) and Energy Balance Tables[32]. Global energy and economic flows for regions other than China and China's international imports and exports are parameterized using the 8th release of the Global Trade Analysis Project data (GTAP)[33]. The primary inputs to production in the dataset include labour, capital and natural resources, with endowments denominated in 2007 US$. To prepare inputs for C-REM, we aggregate commodities into four energy sectors and nine non-energy composites (Supplementary Table 1). Based on general equilibrium theory[34], the model is formulated using the mathematical programming subsystem MPSGE in GAMS[35] and solved at five-year intervals through to 2030. A detailed description of the C-REM model structure and assumptions is provided in Zhang et al.[16] for a static version of the model and Luo et al.[17] for the dynamic version of the model (with the latter used in the present study). To enable a clear comparison of carbon pricing between the business-as-usual (No Policy) and policy scenarios, without its interactions with other policy and technology uncertainties, we do not explicitly model scenarios that vary assumptions on future technological changes or policies that will affect China's development of non-fossil fuel energy (for example, renewable feed-in-tariff adjustments), natural gas (such as expansion of shale gas usage and increased imports of liquified natural gas) and the electrification of transportation (a subsidy for electric vehicles, for example). To represent ongoing improvements in energy efficiency unrelated to energy price changes, we assume in all scenarios an autonomous energy efficiency improvement rate of 1.7% per year in China following Zhang et al.[36]. The autonomous energy efficiency improvement rate is applied to all production sectors and household final demand as an exogenous trend for all provinces. The No Policy scenario through to 2015 is calibrated to historical observations[37], while projections for future periods reflect economic growth assumptions in the Thirteenth Five-Year Plan (2016–2020) and related documents describing the growth trajectories of individual provinces as discussed in Luo et al.[17]. C-REM specifies factor endowments in the base year, labour productivity and population growth rate, but treats economic responses to policies endogenously. Policy is imposed as a constraint on CO_2 intensity that results in a shadow price on CO_2, increasing the relative cost of CO_2-intensive production. Responses to policy are reflected in changes in sectoral outputs, GDP and welfare. Elasticity values in constant-elasticity-of-substitution production functions, which are used to represent technologies and define substitution possibilities among inputs, mediate the extent of these adjustments[16].

Emissions projections. Provincial-level CO_2 and pollutant emissions are computed based on projected energy use and economic activity, multiplied by emissions factors. We compute emissions factors for CO_2 and pollutant species SO_2, NO_x, NH_3, BC and OC in 2007 by province, sector and energy type. We only consider CO_2 emissions from energy combustion, because China's commitment in the Paris Agreement and related policies are primarily targeted at industry-related CO_2 emissions. Emissions factors for CO_2 from combustion are estimated following IPCC guidelines[38]. GHG emissions from non-combustion processes are not considered primarily because they are not the focus of the study (which is to illustrate quantification of co-benefits using the example of energy-related co-benefits of CO_2 mitigation) but also because of a lack of accurate data sources and mitigation cost information for China. On pollutants, we divide provincial pollution quantities reported in the REAS inventory[22] by the corresponding sectoral energy use (for combustion emissions) or activity level (for non-combustion emissions) in C-REM. To ensure consistency in the attribution of emissions between REAS and C-REM, sectors in REAS are aggregated to match the sectors in C-REM. The aggregation consolidates the detailed energy types in REAS into the four energy sectors in C-REM and maps the industrial sectors in REAS into the four C-REM industrial sectors, which include construction (CON), energy intensive industries (EIS), other manufacturing industries (MAN) and metal/non-metal mineral mining (OMN). Supplementary Table 2 illustrates how sectors in REAS are mapped to those in C-REM. For each sector, REAS divides sources into two categories—combustion and non-combustion—for example, 87% of SO_2 comes from combustion sources (mostly due to the use of fossil fuels as production input) and 13% from non-combustion sources, while only 0.4% of NH_3 comes from combustion sources and 99.6% from non-combustion sources. For each sector, we associate combustion emissions with energy use by type and the non-combustion emissions to the activity level (projected quantity of economic output). We divide the emissions quantities in REAS by C-REM model outputs in 2007 to yield emissions factors specific to each pollutant for each economic sector and each province in 2007. Emissions factors due to use of coal in the electricity (ELE) sector are generally smaller than in the other industrial sectors, such as MAN, because the ELE sector in China has access to coal of better quality (that is, a higher heating value and lower sulfur content).

To update the REAS emission inventory in 2007 for more recent years, we calibrate the emissions factors for 2010 and 2015 using available data. The calibration in 2010 is conducted by scaling the emissions factors in this particular year to match national totals in the MEIC inventory[23]. An exception is the emissions factor for NH_3, which we scale to match the data in Streets et al.[39], and we apply an additional 30% reduction, as recommended by Kharol et al.[40], to better match observations. The calibration for 2015 is conducted by scaling the emissions factors to match the extrapolated trend for 2015 defined by the observations for 2010 and 2012 in MEIC, since 2015 data are not yet available. Emissions factors for SO_2, NO_x, NH_3, BC and OC in 2015 are 77%, 72%, 57%, 56% and 53% of their respective levels in 2007.

To account for technology improvement in end-of-pipe solutions that are exogenous to climate policy in China, we assume that emissions factors in all scenarios continue to decrease after 2015. To simulate the evolution of emissions factors over time, we adopt the methodology in Webster et al.[41], in which emissions factors are estimated to decline exponentially in time to match the decreasing historical trend observed in 15 developed countries. The trend parameter (exponential decay constant) of each pollutant is listed in Supplementary Table 3. SO_2 has a slightly faster decay rate compared to other species, reflecting the aggressive deployment of sulfur scrubbers on new power plants. In addition, we assume that the emissions factors related to biomass burning, which contributes substantially to BC and OC, will also have a faster decay rate than other pollutants to represent stricter enforcement of banning the burning of crop residuals in rural areas. This decline in the emissions factors is meant to capture efficiency improvement in end-of-pipe controls for air pollutants, for example, newer sulfur scrubbers may have better removal efficiency, and not to capture accelerated adoption of tailpipe control technologies by the industry that may be triggered by environmental regulations. Emissions factors (tons of SO_2 and NO_x per ton of coal use) in 2030 in our study remain higher than current factors for the United States. For example, the emissions factor of SO_2 in the electricity sector in 2030 in our study is 10% higher than the aggregate US emissions factor in 2015, and that of NO_x is four times the level of the United States in 2015[42,43]. In this study, to isolate co-benefits, we assume that climate policies do not trigger accelerated adoption of end-of-pipe control technologies as policies target only CO_2 emissions. We conducted three additional simulations to examine the sensitivity of emissions in the No Policy scenario to emissions factor changes (refer to Supplementary Fig. 1 and associated discussion).

GEOS-Chem. GEOS-Chem is a global three-dimensional chemical transport model driven by assimilated meteorological data from the Goddard Earth Observation System (GEOS) of the NASA Global Modeling and Assimilation Office (GMAO) (http://www.geos-chem.org/). The aerosol simulation in GEOS-Chem represents an external mixture of secondary inorganic aerosols, carbonaceous aerosols, sea salt and dust aerosols coupled with gas-phase chemistry. For this work, we use version 9-01-03 of GEOS-Chem with a horizontal resolution of $0.5° \times 0.667°$ in East Asia[44]. It has 47 vertical layers from surface to 80 km with 14 layers in the lowest 2 km and a surface layer of 130 m. For our simulations, we corrected errors in night-time mixing depth using the methodology suggested in Walker et al.[45]. Additionally, we reduce the HNO_3 concentration used as input for thermodynamic gas and particle partitioning by 25% at each time step to avoid the overproduction of nitrate, following Heald et al.[46].

To validate the GEOS-Chem simulation of $PM_{2.5}$, we compiled an observational dataset from available publications that includes annual measurements of sulfate, nitrate and ammonium, BC, OC and total $PM_{2.5}$ from 25 sites in China taken between 2005 and 2010[47–51], and compared with simulated concentrations from 2007 or 2010 (whichever year was closer). For sulfate, nitrate and ammonium aerosols, we obtained additional measurements at 26 sites from the Acid Deposition Monitoring Network in East Asia (EANET) in 2010[52], 25 of which are outside China but within our simulation domain. GEOS-Chem generally reproduces the spatial distribution of ambient concentrations of different aerosol species with correlation coefficient (r) between annual mean concentrations of model simulations and observations >0.6 (Supplementary Fig. 2 and Supplementary Table 4). Simulated sulfate and nitrate aerosols are underestimated by about 30%, and BC and OC are underestimated by about 40%, which altogether contribute to an underestimation of total $PM_{2.5}$ by 13% (Supplementary Table 4). The difficulties for atmospheric chemistry models in capturing high concentrations of $PM_{2.5}$ especially in urban areas have been discussed extensively in the literature (for example, see Wang et al.[53]), and can be caused by missing emissions, formation pathways such as in the case of secondary organic aerosols[26] or spatial heterogeneity in emissions, meteorology and chemistry. Since the major $PM_{2.5}$ co-benefits we found in this study are within sulfate–nitrate–ammonium aerosols, co-benefits could be underestimated considering these biases in simulated inorganic aerosols. However, these biases are comparable to or better than biases found in other studies that assess nonlinearities in inorganic aerosol chemistry (for example, Holt et al.[54] and Kharol et al.[40]), and suggest our model is doing as well as possible given the current state of science.

To calculate air quality co-benefits of climate policies, we conducted five GEOS-Chem simulations; one for the 2010 base year, and four scenarios in 2030 (No Policy and three climate policy scenarios). Gridded emissions of SO_2, NO_x, BC and OC in 2010 are generated by scaling gridded REAS emissions in 2007 for each province according to emissions outputs from C-REM model in 2007 and 2010. As mentioned above, we use gridded emissions of NH_3 in 2000 from Streets et al.[39] with a 30% reduction[40] as gridded emissions in 2010. Gridded emissions in 2030 for all scenarios are scaled by province based on emission outputs from C-REM in 2010 and 2030 as described above, reflecting changes in economic structure and patterns of energy use as they evolve over time and adjust in response to policy. The spatial distribution of emissions within provinces does not change over time.

Each simulation is one year long with a six-month spin-up period, and the same meteorological fields for the year 2010 are used in all simulations. We alter only the anthropogenic emissions in China according to C-REM outputs, while emissions in the rest of the world are kept unchanged. $PM_{2.5}$ concentrations reported here are calculated as the sum of sulfate, nitrate, ammonium, BC, OC and dust concentrations following equation (3):

$$PM_{2.5} = 1.33 \times (SO_4 + NIT + NH_4) + BC + 1.8 \times (OCPO + 1.16 \times OCPI) + 1.86 \times SALA + DST1 + DST2 \times 0.38 \quad (3)$$

Where SO_4, NIT and NH_4 represent sulfate–nitrate–ammonium aerosols, OCPO and OCPI represent hydrophobic and hydrophilic organic carbon, and SALA represents accumulation mode sea salt. DST1 and DST2 represent dust with size bins of 0.2–2.0 and 2.0–3.6 μm in diameter, respectively. DST2 is multiplied by 0.38 to reflect the mass fraction of $PM_{2.5}$ in DST2 assuming a log-normal size distribution. To convert dry aerosol concentrations from GEOS-Chem outputs to observed $PM_{2.5}$, which is often under a relative humidity of 35%, scaling factors of 1.33, 1.16 and 1.86 are used for sulfate–nitrate–ammonium, hydrophilic organic carbon and sea salt aerosols, respectively. We use a conversion ratio from OC to organic matter of 1.8 based on measurements in Chinese cities[55]. Anthropogenic $PM_{2.5}$ concentrations are the sum of sulfate, nitrate, ammonium, BC and OC. Secondary organic aerosols are not included in the $PM_{2.5}$ calculation. We report anthropogenic and total $PM_{2.5}$ changes by province in Supplementary Fig. 5.

Health impacts and valuation. We calculate avoided premature deaths associated with reduction in total $PM_{2.5}$ atmospheric concentrations using the 2010 GBD exposure–response relationships, covering the range of levels of global exposure to $PM_{2.5}$[24]. We also use the Environmental Benefits Mapping and Analysis Program–Community Edition (BenMAP-CE)[56] to provide two additional estimates of avoided premature deaths (one using an exposure–response function estimated from Chinese data, and one using an exposure-response function based on US data). For nearly all provinces, the BenMAP-CE results bound the GBD estimate. In five provinces (Guangdong, Fujian, Shanghai, Hainan, Fujian and Xinjiang), the GBD estimate is higher than both BenMAP-CE results, and for Shaanxi it is lower, but all are still within the same order of magnitude.

Following the GBD study, premature mortality due to five disease categories including acute lower respiratory illness (ALRI), chronic obstructive pulmonary disease (COPD), cerebrovascular disease (CEV), ischemic heart disease (IHD) and lung cancer (LC) attributed to ambient $PM_{2.5}$ in 2010 and 2030 was estimated from equation (4) as follows:

$$\Delta Mort = y_0 \times pop \times (1 - 1/RR) \quad (4)$$

where y_0 is the baseline mortality rate for each disease, pop is the population of either children younger than 5 years (ALRI) or adults older than 30 years (COPD, CEV, IHD, and LC) and RR is the relative risk, which is calculated from the exposure response function based on the Ambient Air Pollution Risk Model in the 2010 GBD Study[57].

The 2010 GBD exposure–response relationships, documented in Burnett et al.[24], incorporate epidemiological studies of passive and active smokers to account for high $PM_{2.5}$ concentrations similar to those observed in China. COPD and CEV have different exposure response functions by age group with five-year intervals. We reported median mortality results using 1000 sets of RR values from Monte Carlo simulations.

Baseline mortality rates for each disease and each age group were obtained from the World Health Organization Statistics and Health Information System[58]. Gridded population in 2010 was accessed from the Columbia University Center for International Earth Science Information Network (CIESIN) with a spatial resolution of 0.5° × 0.5°[59]. Populations by country and by age group in 2010 and 2030 are taken from the United Nations World Population Prospects (2015 revision, median fertility scenario)[60]. We assume spatial distribution of population is unchanged in 2030.

We used BenMAP-CE to provide two additional estimates of avoided premature deaths. BenMAP-CE is an open-source program designed by the US EPA and collaborators that calculates health impacts based on changes in air pollutant concentrations, baseline incidence of a health effect, population data and a health effect coefficient that relates a change in air pollutant concentration with a change in incidence[56]. Vorhees et al.[61] provide a proof-of-concept methodology for using BenMAP-CE to perform health impact assessments on China, as well as documentation of the China data included in BenMAP-CE. We used baseline incidence and projected 2030 population data included in the China setup of BenMAP-CE. We used two all-cause mortality health effect coefficients from two epidemiological studies: Cao et al.[62], which provides an exposure–response relationship based on Chinese data for adults older than 40 years, and Krewski et al.[63], which provides an exposure–response relationship based on US data for adults older than 30 years.

Mortality valuations are based on the US EPA methodology and estimates for the VSL, the suggested value of which is US$7.75 million[64]. Methods for calculating the VSL and a review of resulting estimates can be found in Viscusi et al.[65]. The VSL for each Chinese province is based on the ratio of GDP per capita in 2030 relative to GDP per capita in 2007, similar to the procedure in Shindell et al.[12]:

$$VSL = VSL_{base} \times (pcGDP2007_{CHP} / pcGDP2007_{US} \times pcGDP2030_{CHP} / pcGDP2007_{CHP})^{0.4} \quad (5)$$

where $pcGDP_{CHP}$ and $pcGDP_{US}$ represent GDP per capita in 2007 (or 2030) for each Chinese province and the US, respectively. Income elasticity of the VSL with respect to per capita GDP is set to be 0.4[66].

For comparison, we also calculate co-benefits using a VSL based on Chinese data[67], which corresponds to a year 2007 VSL of US$165,600 with an income elasticity of 0.42. Calculated health benefits using this VSL are US$12.1 billion, US$32.6 billion and US$55.6 billion in the 3% Policy, 4% Policy and 5% Policy cases, respectively.

Code availability. The code for data analysis and plotting can be accessed at http://svante.mit.edu/~mwli/Li_and_Zhang_2018.

Data availability. The modelling results and data can be accessed at http://svante.mit.edu/~mwli/Li_and_Zhang_2018.

References

31. *The China Regional Input–Output Tables 2007* (National Bureau of Statistics of China, 2011).
32. *China Energy Statistical Yearbook 2008* (National Bureau of Statistics of China, 2011).
33. Narayanan, G. B., Aguiar, A. & McDougall, R. *Global Trade, Assistance, and Production: The GTAP 8 Data Base* (Center for Global Trade Analysis, Purdue University, 2012).
34. Arrow, K. J. & Debreu, G. Existence of an equilibrium for a competitive economy. *Econometrica* **22**, 265–290 (1954).
35. Rutherford, T. F. Applied general equilibrium modeling with MPSGE as a GAMS subsystem: an overview of the modeling framework and syntax. *Comput. Econ.* **14**, 1–46 (1999).
36. Zhang, X., Karplus, V. J., Qi, T., Zhang, D. & He, J. Carbon emissions in China: How far can new efforts bend the curve? *Energy Econ.* **54**, 388–395 (2016).
37. *China Statistical Database* (National Bureau of Statistics of China, 2012).
38. *2006 IPCC Guidelines for National Greenhouse Gas Inventories* (IPCC, 2006).
39. Streets, D. G. et al. An inventory of gaseous and primary aerosol emissions in Asia in the year 2000. *J. Geophys. Res.* **108**(D21), 8809 (2003).
40. Kharol, S. K. et al. Persistent sensitivity of Asian aerosol to emissions of nitrogen oxides. *Geophys. Res. Lett.* **40**, 1021–1026 (2013).
41. Webster, M., Paltsev, S., Parsons, J., Reilly, M. J. & Jacoby, H. D. *Uncertainty in Greenhouse Gas Emissions and Costs of Atmospheric Stabilization* Report No. 165 (MIT Joint Program on the Science and Policy of Global Change, 2008).
42. *Quarterly Coal Report April–June 2017* (US Energy Information Administration, 2017).
43. *Air Pollutant Emissions Trends Data* (US Environmental Protection Agency, 2016); https://www.epa.gov/air-emissions-inventories/air-pollutant-emissions-trends-data
44. Wang, Y. X., McElroy, M. B., Jacob, D. J. & Yantosca, R. M. A nested grid formulation for chemical transport over Asia: Applications to CO. *J. Geophys. Res.* **109**, D22307 (2004).
45. Walker, J. M., Philip, S., Martin, R. V. & Seinfeld, J. H. Simulation of nitrate, sulfate, and ammonium aerosols over the United States. *Atmos. Chem. Phys.* **12**, 11213–11227 (2012).
46. Heald, C. L. et al. Atmospheric ammonia and particulate inorganic nitrogen over the United States. *Atmos. Chem. Phys.* **12**, 10295–10312 (2012).
47. Zhang, X. Y. et al. Atmospheric aerosol compositions in China: Spatial/temporal variability, chemical signature, regional haze distribution and comparisons with global aerosols. *Atmos. Chem. Phys.* **12**, 779–799 (2012).
48. He, K. et al. Spatial and seasonal variability of $PM_{2.5}$ acidity at two Chinese megacities: insights into the formation of secondary inorganic aerosols. *Atmos. Chem. Phys.* **12**, 1377–1395 (2012).

49. Xu, L. et al. Seasonal variations and chemical compositions of $PM_{2.5}$ aerosol in the urban area of Fuzhou, China. *Atmos. Res.* **104-105**, 264–272 (2012).
50. Zhao, P. S. et al. Characteristics of concentrations and chemical compositions for $PM_{2.5}$ in the region of Beijing, Tianjin, and Hebei, China. *Atmos. Chem. Phys.* **13**, 4631–4644 (2013).
51. Zhang, R. et al. Chemical characterization and source apportionment of $PM_{2.5}$ in Beijing: seasonal perspective. *Atmos. Chem. Phys.* **13**, 7053–7074 (2013).
52. *Acid Deposition Monitoring Network in East Asia* (Asia Center for Air Pollution Research, 2012); http://www.eanet.asia/product/index.html
53. Wang, Y. et al. Enhanced sulfate formation during China's severe winter haze episode in January 2013 missing from current models. *J. Geophys. Res. Atmos.* **119**, 10425–10440 (2014).
54. Holt, J., Noelle, E. S. & Susan, S. Changes in inorganic fine particulate matter sensitivities to precursors due to large-scale US emissions reductions. *Environ. Sci. Technol.* **49**, 4834–4841 (2015).
55. Xing, L. et al. Seasonal and spatial variability of the OM/OC mass ratios and high regional correlation between oxalic acid and zinc in Chinese urban organic aerosols. *Atmos. Chem. Phys.* **13**, 4307–4318 (2013).
56. *Environmental Benefits Mapping and Analysis Program–Community Edition User's Manual* (RIT International, 2015).
57. *Global Burden of Disease Study 2010: Ambient Air Pollution Risk Model 1990–2010* (Institute for Health Metrics and Evaluation, 2013); http://ghdx.healthdata.org/record/global-burden-disease-study-2010-gbd-2010-ambient-air-pollution-risk-model-1990-2010
58. *WHOSIS: Detailed Data Files of the WHO Mortality Database* (World Health Organization, 2015); http://www.who.int/healthinfo/statistics/mortality_rawdata/en/
59. *Gridded Population of the World* Version 3 (Center for International Earth Science Information Network, 2005); http://sedac.ciesin.columbia.edu/data/set/gpw-v3-population-count-future-estimates
60. *World Population Prospects: The 2015 Revision* (United Nations, Department of Economic and Social Affairs, Population Division, 2015).
61. Voorhees, A. S. et al. Public health benefits of reducing air pollution in Shanghai: a proof-of-concept methodology with application to BenMAP. *Sci. Total Environ.* **485–486**, 396–405 (2014).
62. Cao, J. et al. Association between long-term exposure to outdoor air pollution and mortality in China: a cohort study. *J. Hazard. Mater.* **186**, 1594–1600 (2011).
63. Krewski, D. et al. *Extended Follow-Up and Spatial Analysis of the American Cancer Society Study Linking Particulate Air Pollution and Mortality* Report No. 140 (Health Effects Institute Research, 2009).
64. *Guidelines for Preparing Economic Analyses* (US EPA, 2014); https://yosemite.epa.gov/ee/epa/eerm.nsf/vwAN/EE-0568-50.pdf/$file/EE-0568-50.pdf
65. Viscusi, W. K. in *Handbook of the Economics of Risk and Uncertainty* Vol. 1 (eds Machina, M. & Viscusi, W. K.) 385–452 (Elsevier, Amsterdam, 2014).
66. Hammitt, J. K. & Robinson, L. A. The income elasticity of the value per statistical life: transferring estimates between high and low income populations. *J. Ben. Cost. Anal.* **2**, 1–29 (2011).
67. Wang, H. & He, J. J. *The Value of a Statistical Life: A Contingent Investigation in China* Working Paper 5421 (The World Bank Development Research Group, 2010); http://elibrary.worldbank.org/doi/abs/10.1596/1813-9450-5421