ARTICLES
https://doi.org/10.1038/s41893-019-0398-8
nature sustainability

Air quality and health benefits from fleet electrification in China

Xinyu Liang[1,5], Shaojun Zhang[1,2,5], Ye Wu[1,3*], Jia Xing[1,3], Xiaoyi He[4], K. Max Zhang[2], Shuxiao Wang[1,3] and Jiming Hao[1,3]

China has emerged as a leading electric vehicle (EV) market, accounting for approximately half of the global EV sales volume. We employed an atmospheric chemistry model to evaluate the air quality impacts from multiple scenarios by considering various EV penetration levels in China and assessed the avoided premature mortality attributed to fine particulate matter and ozone pollution. We find higher fleet electrification ratios can synergistically deliver greater air quality, climate and health benefits. For example, electrifying 27% of private vehicles and a larger proportion of certain commercial fleets can readily reduce the annual concentrations of fine particulate matter, nitrogen dioxide and summer concentrations of ozone by 2030. This scenario can reduce the number of annual premature deaths nationwide by 17,456 (95% confidence interval: 10,656–22,160), with the Beijing–Tianjin–Hebei, Yangtze River Delta and Pearl River Delta regions accounting for ~37% of the total number. The high concentration of health benefits in populous megacities implies that their municipal governments should promote more supportive local incentives. This study further reveals that fleet electrification in China could have more health benefits than net climate benefits in the next decade, which should be realized by policymakers to develop cost-effective strategies for EV development.

Electric vehicles (EVs) have the potential to not only improve energy efficiency in the transportation sector but also accommodate renewable power sources (for example, solar, wind and hydroelectricity)[1,2], making them an essential policy component for addressing global climate change. The International Energy Agency suggests that global EV sales will need to climb to 43 million (approximately 30% of total vehicle sales, excluding two- and three-wheelers) by 2030[3] to achieve the Paris Agreement's climate target of limiting global warming to 2 °C. In the past decade, diversified EV policies and measures, including purchase subsidies, tax exemptions, fuel economy regulations and favourable transportation policies, have been adopted by many national and local governments across the world[3–5]. In addition, because battery production costs have been substantially reduced, total global EV sales reached approximately 2 million in 2018 (excluding two- and three-wheelers and low-speed electric vehicles), after having reached the 1 million mark in 2017[3]. China has become the most important driver in the global EV market and has accounted for half of the global sales volume since 2017[3]. Notably, according to the latest industrial statistics, annual EV sales in China exceeded 1 million for the first time in 2018, achieving more than a 60% increase compared with EV sales in 2017[6].

EVs are expected to mitigate urban atmospheric pollution and the health impacts caused by fossil-fuel-powered internal combustion engine vehicles (ICEVs)[7–9]. Notably, several European countries have announced plans to eliminate ICEV sales in the future[10], mainly due to high real-world nitrogen oxides (NO_x) emissions and the associated health impacts of diesel vehicles[11,12]. The post-2020 carbon dioxide (CO_2) emission regulations in combination with the real-driving-emission regulations for light-duty vehicles in Europe will increase the manufacturing costs of ICEVs and at the same time are likely to expedite fleet electrification in the near future[13,14]. However, there are reservations regarding the role of EVs in improving air quality. EVs reduce exhaust emissions of air pollutants on roads but may lead to increased emissions from electricity production processes[15,16]. These concerns are more pronounced in China, where power generation is more heavily dependent on coal-fired units than that in Europe and the United States. Therefore, it is even more important to evaluate the air quality impacts of fleet electrification in the country with the largest EV market.

Advanced air quality models have been recently employed to evaluate the impacts of fleet electrification in various countries and regions[7–9,17–19]. These models have addressed the spatial heterogeneity of emission changes between road and power sectors and the complicated atmospheric formation of secondary pollutants caused by EV deployment. EVs may also reduce ambient nitrogen dioxide (NO_2) concentrations, especially at traffic-dense sites, where NO_2 air quality standards may be exceeded[7,9]. The impacts on secondary air pollutants, in particular, fine particulate matter ($PM_{2.5}$) and ozone (O_3), can vary greatly due to the penetration of clean electricity, the proximity to power plants and atmospheric conditions[7–9,17–19]. Although the Chinese government's ambition regarding EV promotion is partially driven by serious air pollution problems[20], policymakers have not been explicitly informed of the potential impacts on air quality and human health nationwide. Consequently, until now, the systematic and comprehensive evaluation of air quality and the health benefits of fleet electrification have been absent during the process of designing governmental EV subsidies in China.

In this paper, we began with scenario development of the future penetration of EV technologies in China through 2030. One plausible scenario of fleet electrification, Scenario EV, assumed that 27% of private passenger vehicles and higher percentages of certain

[1]School of Environment, State Key Joint Laboratory of Environment Simulation and Pollution Control, Tsinghua University, Beijing, China. [2]Sibley School of Mechanical and Aerospace Engineering, Cornell University, Ithaca, NY, USA. [3]State Environmental Protection Key Laboratory of Sources and Control of Air Pollution Complex, Beijing, China. [4]School for Environment and Sustainability, University of Michigan, Ann Arbor, MI, USA. [5]These authors contributed equally: Xinyu Liang, Shaojun Zhang. *e-mail: ywu@tsinghua.edu.cn

commercial fleets will be EVs. We applied a multisector emission inventory to estimate the emission changes of the major air pollutants between Scenario EV and a scenario without EV penetration (Scenario w/o EV). The uncertainties in future EV penetration rates were addressed by developing four additional scenarios with varying levels of EV adoption to quantify the associated environmental, health and climate impacts (Discussion). Next, we employed an atmospheric chemistry transport model to evaluate the ambient concentration changes of $PM_{2.5}$, O_3 and NO_2 between fleet electrification scenarios and Scenario w/o EV in China. Fine-scale simulations were conducted for the three developed regions in East China to characterize the air quality impacts in urban areas and their rural counterparts. Finally, the health impacts of fleet electrification were assessed in terms of avoided mortality attributed to long-term $PM_{2.5}$ and O_3 exposure, which was further expressed in monetary values to compare with the climate benefits of mitigating greenhouse gas (GHG) emissions. Following this framework, we conducted a comprehensive sensitivity analysis by considering the uncertainties in power sources of future electricity generation and different modelling methods regarding spatial resolution, exposure–response function and value of statistical life (VSL; Supplementary Note 2 and Methods).

Future emission changes due to fleet electrification

Taking Scenario EV, for example, the total electrification rate is projected by incorporating the growth in the light-duty passenger vehicle (LDPV) fleet and other commercial fleets, which consist of 32 million plug-in hybrid electric vehicles (PHEVs) and 54 million battery electric vehicles (BEVs) (Supplementary Table 5). A total of approximately 80 million electric LDPVs are expected to be on the road by 2030. The emission reductions by vehicle category and increased emissions at power plants in China and the three regions are quantified (Supplementary Table 8). Conventional LDPVs are powered by gasoline engines and emit a considerable amount of non-methane volatile organic compounds (NMVOCs; estimated at 1.6 million t without electrification) in China. Electrification at this scale will substantially reduce NMVOC emissions from on-road vehicles, while the increase in power plants will be small. However, electrifying public buses, medium- and heavy-duty passenger vehicles (MDPVs and HDPVs) and light-duty trucks (LDTs; for urban logistics) will contribute more to NO_x emission reductions than will electrifying LDPVs. This is because most of these commercial vehicles use diesel engines, and NO_x emission control under congested urban conditions is very challenging for diesel engines[4]. Thus, total on-road NO_x emissions would be reduced by 0.84 million t in 2030, though the charging load would slightly increase NO_x emissions and partially offset the benefits of on-road EVs (Supplementary Tables 6 and 7). Notably, NO_x emission changes between on-road and power plant sectors also differ spatially. The urban emission reduction from on-road vehicles will directly alleviate ambient NO_2 concentrations; however, large power plants, which are often built outside urban areas, will have a smaller impact on urban NO_2 concentrations. As Supplementary Table 8 summarizes, electrifying on-road vehicles would reduce the total emissions of all gaseous precursors except sulfur dioxide (SO_2) in the three developed regions. It is estimated that fleet electrification will slightly increase the total emissions of primary $PM_{2.5}$ nationwide but lead to emission reductions in the three developed regions. This is because the three developed regions are power-loading centres, which in part rely on interprovincial electricity transmission. Although EVs would produce lower net $PM_{2.5}$ emissions in these developed regions, they could produce higher net $PM_{2.5}$ emissions if considering the additional emissions from electricity supplied to these regions by other provinces. The detailed emissions for on-road vehicles and power plants under other scenarios are provided in Supplementary Tables 6 and 7.

Impacts on regional and urban air quality

We estimate that by 2030, fleet electrification in Scenario EV will deliver a consistent reduction in $PM_{2.5}$ concentrations nationwide (Fig. 1) relative to Scenario w/o EV, and the concentration reductions in the three developed regions are higher. The air quality simulation results indicate that annual average area-wide $PM_{2.5}$ concentrations could decrease by $0.33 \pm 0.17\,\mu g\,m^{-3}$, $0.35 \pm 0.16\,\mu g\,m^{-3}$ and $0.32 \pm 0.18\,\mu g\,m^{-3}$ (note that uncertainty ranges for concentrations represent standard deviations) in the Beijing–Tianjin–Hebei (JJJ), Yangtze River Delta (YRD) and Pearl River Delta (PRD) regions, respectively. These represent concentration reductions of 1.7%, 1.7% and 2.8%, respectively, compared with those under the Scenario w/o EV. Greater mitigation is found to occur in urban areas, which can reach 0.43 ± 0.23 (1.9%), 0.44 ± 0.20 (1.8%) and 0.44 ± 0.22 (3.1%) $\mu g\,m^{-3}$ in the JJJ, YRD and PRD regions, respectively. The geographic distributions of $PM_{2.5}$ concentration changes under other fleet electrification scenarios are presented in the Supplementary Note 2.1 (Supplementary Fig. 2). They suggest that higher ratios of EV penetration can readily lead to greater reductions in ambient $PM_{2.5}$ concentrations.

The annual average reductions in $PM_{2.5}$ concentrations in each region and in major cities (Beijing, Tianjin, Shanghai, Hangzhou, Guangzhou and Shenzhen) are compared and are further separated into two land types (urban versus rural; Supplementary Table 9). We clearly observe greater $PM_{2.5}$ abatements within the urban areas than in rural areas, which reflects the concentrated electrified mileages in urban areas. Thus, considering the demographic characteristics, the annual average population-weighted $PM_{2.5}$ reductions are estimated to be $0.49 \pm 0.15\,\mu g\,m^{-3}$, $0.44 \pm 0.11\,\mu g\,m^{-3}$ and $0.48 \pm 0.10\,\mu g\,m^{-3}$ in the JJJ, YRD and PRD regions, respectively.

Regardless of the season, most of the total $PM_{2.5}$ reductions in urban areas across all three regions come from secondary aerosols rather than from primary components (for example, elementary carbon; Supplementary Fig. 7). In January, reduced nitrate concentrations would be comparable to or greater than secondary organic aerosol (SOA) in the three regions because low temperature favours nitrate formation due to enhanced gas–particle partitioning and other chemical mechanisms. Nitrate reduction also contributes to lower ammonium aerosol concentrations. For other months (May, August and November), SOA is found to be the primary contributor to the total $PM_{2.5}$ reductions because of increased atmospheric oxidants (for example, O_3). The delayed time between emissions of aerosol precursors and the formation of secondary aerosols as well as wind transport would weaken the spatial correlations between each other. As a result, the spatial discrepancy between urban and rural $PM_{2.5}$ concentrations is less significant than that in NO_2 concentrations (Supplementary Table 9), which spatially follow the patterns of on-road NO_x emission reductions.

In addition to reducing $PM_{2.5}$ concentrations, fleet electrification can effectively reduce urban NO_2 concentrations (Fig. 2). The highest NO_2 reductions will occur in the most populous core cities in the three regions (for example, Beijing, Shanghai and Guangzhou). The annual average NO_2 concentrations are estimated to decrease by $1.6 \pm 0.3\,\mu g\,m^{-3}$, $3.9 \pm 0.6\,\mu g\,m^{-3}$ and $1.6 \pm 0.3\,\mu g\,m^{-3}$ for Beijing, Shanghai and Guangzhou, respectively. This represents city-level NO_2 reductions of ~15%–19%. In particular, NO_2 concentration reductions are estimated to be $3.7 \pm 0.7\,\mu g\,m^{-3}$, $5.2 \pm 0.8\,\mu g\,m^{-3}$ and $4.1 \pm 0.7\,\mu g\,m^{-3}$ in the urban areas of these megacities, respectively. This is because more passenger vehicles using internal combustion engines will be replaced by EVs, notably commercial passenger vehicles (for example, public buses, MDPVs and HDPVs) that used to be primarily powered by diesel engines (for example, under Scenario w/o EV). Thus, annual reductions in city-level, population-weighted NO_2 concentration are $4.5 \pm 0.5\,\mu g–m^{-3}$, $5.0 \pm 0.8\,\mu g\,m^{-3}$ and $4.1 \pm 0.7\,\mu g\,m^{-3}$ for Beijing, Shanghai and Guangzhou due to the co-location of NO_2 reductions and population in these megacities.

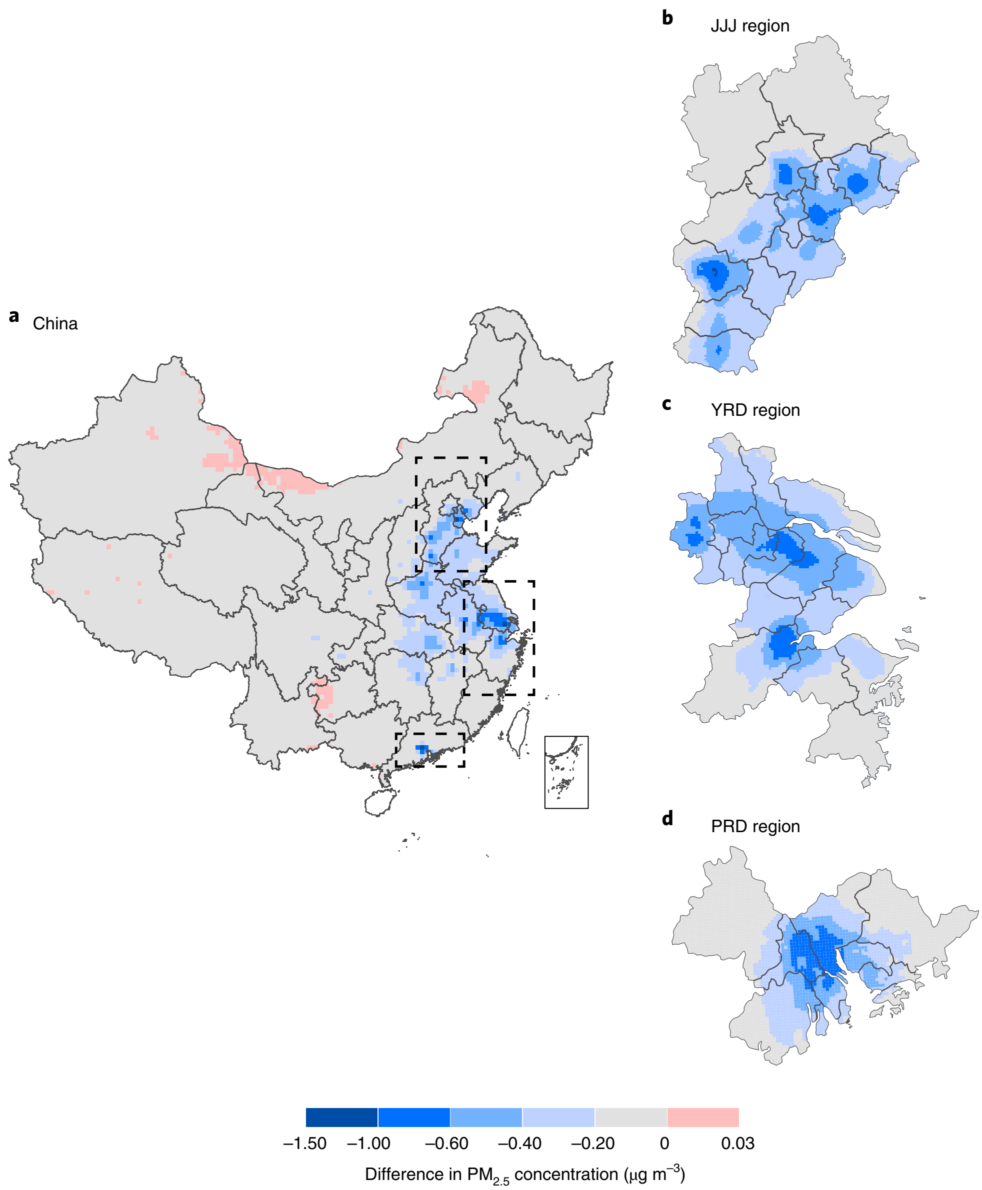

Fig. 1 | Changes in annual average $PM_{2.5}$ concentration in Scenario EV compared with Scenario w/o EV. a–d, The difference in annual average $PM_{2.5}$ concentration between Scenario EV and Scenario w/o EV in China (**a**) and the three regions: JJJ (**b**), YRD (**c**) and PRD (**d**). Three dashed boxes depict the location of the three regions. The deeper blue colour in the panels represents higher $PM_{2.5}$ concentration reduction benefits. See Supplementary Fig. 8 for the $PM_{2.5}$ concentration under the Scenario w/o EV. Chinese county maps obtained from the Beijing City Lab (https://www.beijingcitylab.com) and Chinese provincial map adapted from ref. [59], Elsevier.

Since 2013, mitigating ambient $PM_{2.5}$ concentrations has become a top priority in the Chinese government's efforts to improve air quality, which has resulted in reduced $PM_{2.5}$ concentrations in many cities of China. However, the reduction pace of ambient NO_2 concentrations has been relatively slow compared with that of $PM_{2.5}$, particularly at urban or traffic monitoring sites. The exceedance of the National Ambient Air Quality Standard (an annual limit of 40 μg m^{-3}) for NO_2 has become one of the major air quality issues in many large Chinese cities. The considerable risks of not meeting the annual limit of ambient NO_2 concentrations are estimated in Scenario w/o EV for many urban areas if EVs are not widely deployed by 2030 (Supplementary Fig. 9). This result reveals that EV deployment can result in significant air quality benefits in certain hotspots, such as traffic-dense metropolitan urban areas where the exceedance risk is likely to be high.

Fleet electrification is estimated to result in widespread decreases in summer (May and August) ground-level 8 h maximum O_3 concentrations in the three regions (Fig. 3). Only a small number of areas within and surrounding Shanghai would see increased summer O_3 concentrations (by less than 0.5 ppb on average). The greatest reductions are estimated to appear in Beijing and Guangzhou (both up to 3 ppb), where the on-road emissions of precursors (NMVOC and NO_x) will decrease rapidly through electrifying on-road vehicles. The impacts on winter O_3 concentrations from electrification are more complicated: slight decreases in regional O_3 concentrations and obvious increases in traffic-dense urban areas (increases below 2 ppb). The nonlinear responses of O_3 production to precursors are typically different between urban (VOC-limited conditions) and rural areas (NO_x-limited conditions)[9,21], and the titration of O_3 by NO becomes more important during winter when the NO_2 photolysis rate is lower than in the summer. Using EVs in

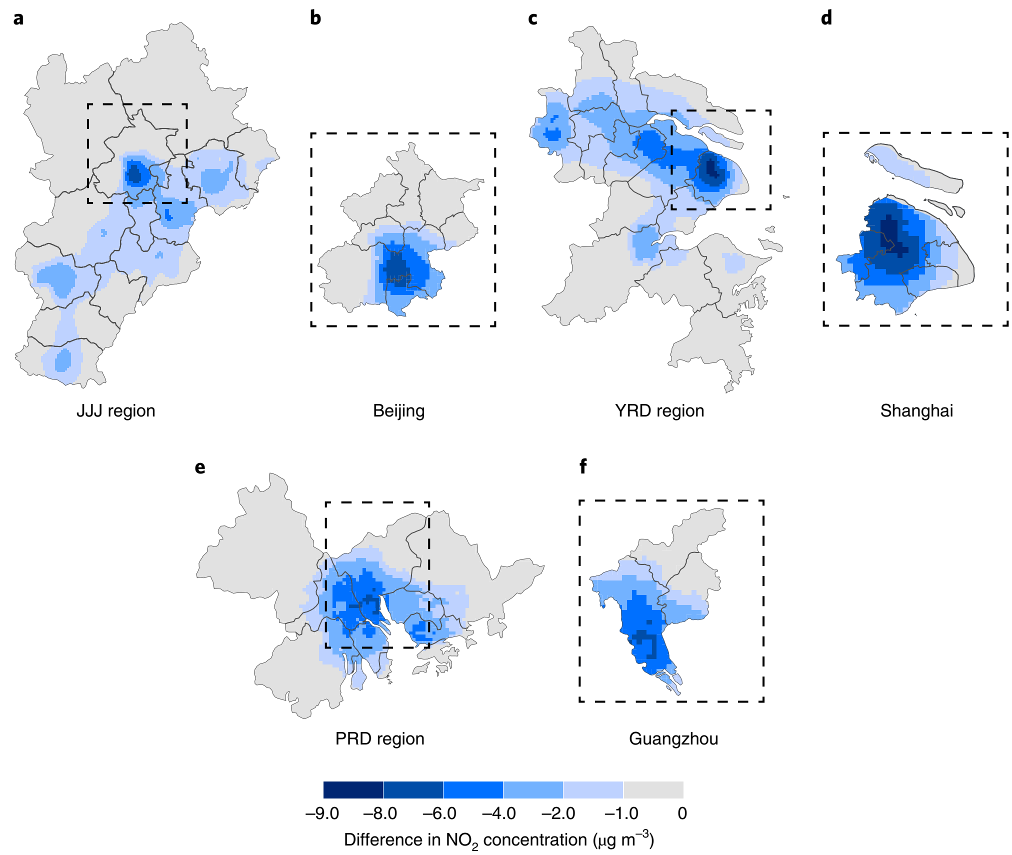

Fig. 2 | Changes in annual average NO_2 concentration in Scenario EV compared with Scenario w/o EV. a–f, The difference in annual average NO_2 concentration between Scenario EV and Scenario w/o EV in three regions (JJJ (**a**), YRD (**c**) and PRD (**e**)) and core cities (Beijing (**b**), Shanghai (**d**) and Guangzhou (**f**)). The deeper blue colour in the panels represents higher NO_2 concentration reduction benefits. See Supplementary Fig. 9 for the NO_2 concentration under Scenario w/o EV and Scenario EV. Chinese county maps and city maps obtained from the Beijing City Lab (https://www.beijingcitylab.com).

urban areas could reduce the titration effect, leading to unwanted increases in ground-level O_3 concentrations that partially offset the benefits of $PM_{2.5}$ and NO_2 reductions. That O_3 concentrations may increase in certain areas and months is consistent with previous studies in the United States and Europe[9,18].

Human health benefits of fleet electrification

Scenario EV can potentially result in significant human health benefits, primarily due to consistent reductions in annual $PM_{2.5}$ and summer O_3 concentrations across the regions. We estimate that 17,456 (95% CI: 10,656–22,160) premature deaths may be avoided in 2030 due to reduced long-term exposure to air pollution (annual $PM_{2.5}$ and summer O_3). The three developed regions account for approximately 37% of the total number of avoided premature deaths nationwide. The estimated 2,634 (1,609–3,317), 2,097 (1,297–2,637) and 1,658 (989–2,150) premature deaths due to long-term exposure can be avoided in the JJJ, YRD and PRD regions, respectively, via fleet electrification. $PM_{2.5}$-attributable benefits could account for 76–80% of the total avoided premature deaths across the three regions, with a small part of this benefit contributed by the lowered summer O_3 concentrations (Supplementary Table 12).

Human health benefits are unevenly distributed, with the most significant numbers of premature deaths being avoided in the urban areas of major cities (Fig. 4). Because urban areas have a much higher population density, the estimates of health benefits per 1,000 km^2 in urban areas (60 to 110 avoided premature deaths at the regional level; Supplementary Fig. 11a) are substantially higher than in rural areas by one to two orders of magnitude. Thus, our results clearly demonstrate that as more electrification deployment is promoted in urban areas in China, many residents there will benefit. Controlling for population density, the estimates of avoided premature deaths per million people in the urban areas are still higher than those of rural areas by 9–66% across the three developed regions (Supplementary Fig. 11b). This result can be explained partly by the greater density of traffic emissions in urban areas and partly by the tendency of power plants to be located outside urban areas.

We further compare the monetary benefits due to human health benefits and well-to-wheels (WTW) GHG emission reductions (Fig. 4). We estimate that the economic benefits of combining health benefits and GHG emission reduction due to fleet electrification are US\$3.5 billion, US\$3.8 billion and US\$2.5 billion (in 2015 value) in the JJJ, YRD and PRD regions, respectively. Therefore, the average benefits per capita will be US\$26.6, US\$30.9 and US\$36.7 for these regions, which accounts for approximately 1–2‰ of the projected GDP per capita in China[22]. The results also reveal that the health benefits of fleet electrification are greater than the net climate benefits expected in the next decade. We note that using different health risk functions and monetization methods will consistently result in greater estimates of the health benefits than of the net climate benefits (Discussion).

Discussion

China has an ambitious agenda to mitigate total GHG emissions not only by electrifying on-road vehicles but also by promoting non-fossil energy sources for the power system. We acknowledge that the air quality benefit is relevant to the cleanness of marginal

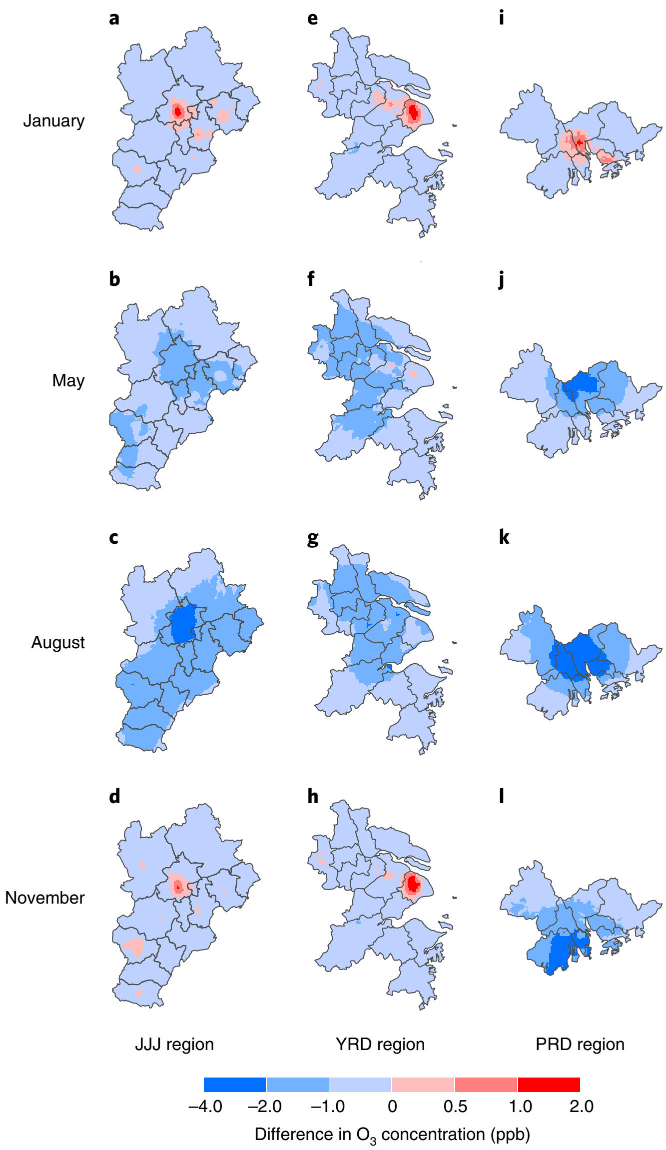

Fig. 3 | Changes in the monthly average 8 h maximum O_3 concentration in Scenario EV compared with Scenario w/o EV. a–l, The difference in O_3 concentration between Scenario EV and Scenario w/o EV in three regions (JJJ (**a**–**d**), YRD (**e**–**h**) and PRD (**i**–**l**)) in January (**a**,**e**,**i**), May (**b**,**f**,**j**), August (**c**,**g**,**k**) and November (**d**,**h**,**l**). See Supplementary Fig. 10 for the O_3 concentration under Scenario w/o EV. Chinese county maps obtained from the Beijing City Lab (https://www.beijingcitylab.com).

electricity, which varies temporally (for example, peak period versus off-peak period) and spatially (for example, more coal-intensive grid electricity in North China). For example, overnight slow charging could take advantage of the wind energy that is highly available during off-peak hours[23]. However, we do not have such detailed profiles regarding charging loads and electricity generation in the entire country. Given this constraint, we examined the sensitivity of using two extreme cases to understand the uncertainty due to different marginal electricity situations. We assumed that the marginal electricity for charging EVs was generated purely on the basis of coal or renewable energy, respectively. The uncertainty from varying marginal electricity is small, as the approximated relative changes of ±0.5% and ±5% for the annual $PM_{2.5}$ and NO_2 concentrations, respectively, are estimated in comparison with Scenario EV (Supplementary Fig. 12). This is because the two major precursors, NMVOC and NO_x, could be largely removed from urban areas; by contrast, large-scale coal-fired power units are not primarily operated in urban areas, and they meet the most stringent regulations in the world and are strictly monitored by continuous emission monitoring systems[24]. Owing to the rapid progress in flue gas controls for power plants, life-cycle assessments indicate that electric cars and buses could substantially reduce WTW emissions of NMVOC and NO_x[16]. However, we note the necessity of promoting renewable electricity to achieve greater GHG emissions mitigation and other sustainability benefits (for example, to reduce water consumption)[25]. Future vehicle-to-grid technologies in return have the potential to stabilize the grid and facilitate economic use of fluctuating renewable power sources[23,26].

Different marginal electricity generation sources could further affect the estimates of avoided premature deaths (Supplementary Fig. 13). The changes in prevented deaths range from approximately ±3% to ±10% for all three developed regions, emphasizing the importance of clearing up mobile emission sources in populous areas. However, the modelling resolution could be a source of uncertainty for the assessment of health impacts (Supplementary Fig. 14). For example, if we opt to use coarser-scale modelling configurations (36 km × 36 km or 12 km × 12 km) for the three developed regions, the reduction of population-weighted $PM_{2.5}$ concentrations would be overestimated in YRD and PRD (possibly caused by the effect of artificial mixing at the coarse spatial resolution) but significantly underestimated in Beijing by up to 30%. Meanwhile, the variability of O_3 reduction due to various spatial resolution configurations is even greater than that of $PM_{2.5}$ because the coarser modelling configurations might not be capable of resolving the VOC-limited conditions in urban centres. Given the heterogeneity of the population density and the air quality benefits between urban and rural areas, we suggest that finer-grained modelling of up to 1 km resolution be applied to certain EV capitals[27]; it needs to further take advantage of real-world, big datasets regarding traffic activity, charging behaviours and electricity generation[23,28,29].

Four future scenarios reflecting different fleet electrification rates were created, taking into account varying favourable levels of incentive policy, technology improvement and consumer preferences (Supplementary Note 2.1). The multi-scenario analysis confirms that higher fleet electrification ratios can positively improve air quality and deliver greater co-benefits of avoided premature deaths and mitigated GHG emissions. Under the least-favourable Scenario EV-LOW (that is, lower electrification rate compared with Scenario EV), the population of EVs for each vehicle category is estimated to decrease to one-half compared with that under Scenario EV, leading to a decline of 41% in the estimate of avoided premature deaths nationwide. However, the most-favourable Scenario EV-PTC (that is, more supportive policies, more technological improvements, and stonger consumer preference to buy EVs than the conditions under Scenario EV) estimates substantially higher EV penetrations for LDPVs (52%, excluding taxis) and LDTs (30%) than those under Scenario EV, which could result in an increase of 46% in the estimate of avoided premature deaths nationwide. For the JJJ region, using fine-scale air quality simulations, the total economic benefits, including air quality improvement and GHG emission mitigation, show a similar change from −40% under Scenario EV-LOW to +51% under Scenario EV-PTC, relative to Scenario EV.

The changes in the avoided premature deaths are estimated using different methods of quantifying the relative risk in $PM_{2.5}$ pollution exposure (Supplementary Notes 2.2). In addition to the global exposure mortality model (GEMM) that we employ in this study, the Global Burden of Disease (GBD) project is another popular method used to estimate $PM_{2.5}$-related mortality worldwide. Using the relative risk functions in the GBD 2017, Scenario EV is estimated to avoid 5,819 (3,962–6,638) $PM_{2.5}$-related premature deaths compared with Scenario w/o EV (13,459 (8,982–16,807) avoided premature

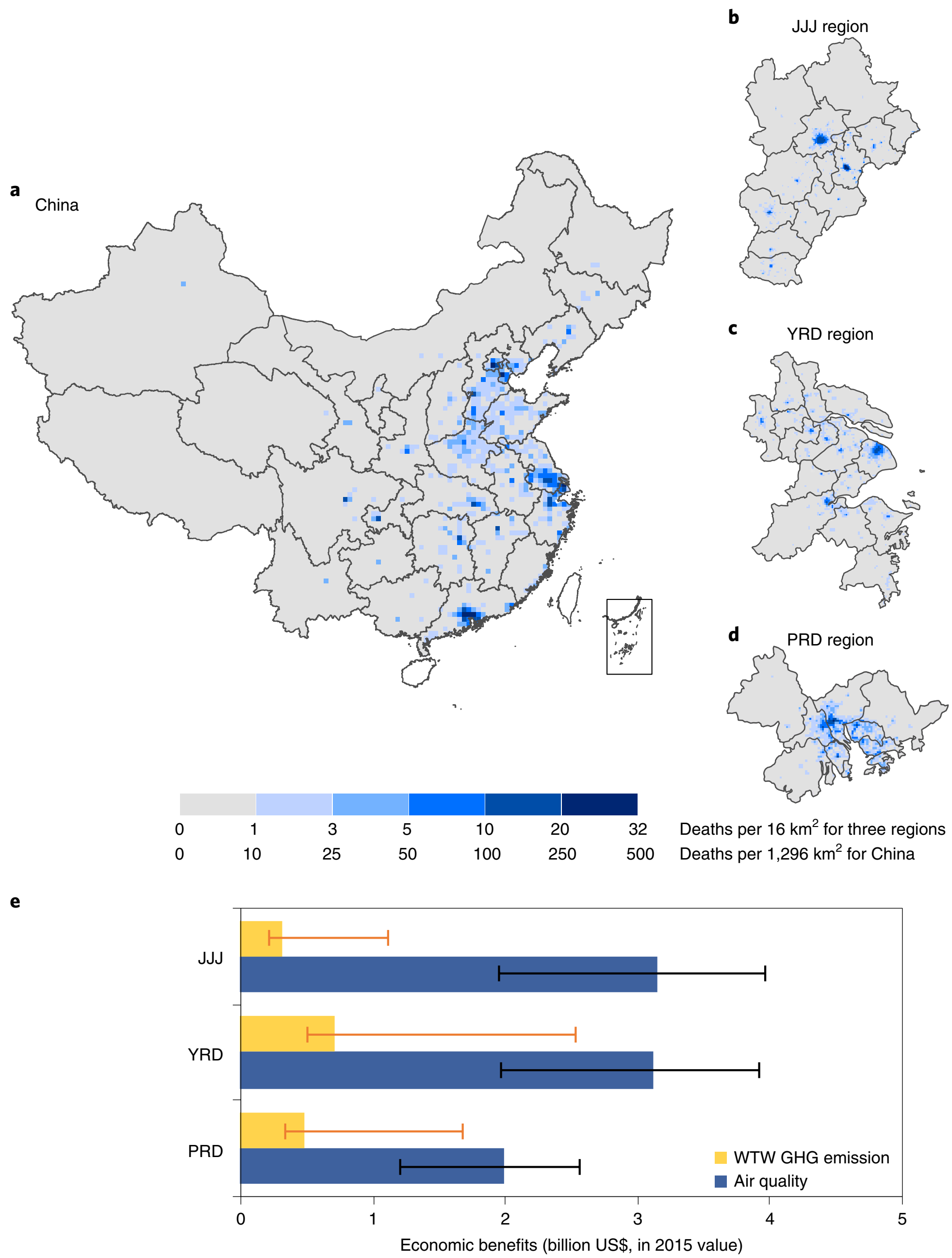

Fig. 4 | Avoided premature deaths and economic benefits in Scenario EV compared with Scenario w/o EV. a–d, Spatial distribution of avoided premature deaths related to long-term air pollution exposure (annual $PM_{2.5}$ and summer O_3) in China (**a**) and the three regions: JJJ (**b**), YRD (**c**) and PRD (**d**). **e**, Economic benefits of both air quality-related health benefits and decreasing WTW GHG emissions in the three regions. Application of the 95% confidence intervals for relative risk (Supplementary Table 10 and Supplementary Fig. 4) to estimate the interval for monetary benefits of air quality benefits. The intervals for economic benefits of decreasing WTW GHG emissions were estimated using US\$33 per tCO_2e and US\$167 per tCO_2e. The central estimate in this study was assumed to be US\$47 (in 2015 value) per tCO_2e. The estimation of CO_2e (CO_2, CH_4 and N_2O are included) was based on global warming potential over a 100 yr time horizon published by the IPCC Fifth Assessment Report[58]. Chinese county maps obtained from the Beijing City Lab (https://www.beijingcitylab.com) and Chinese provincial map adapted from ref. [59], Elsevier.

deaths estimated by using the GEMM functions; Supplementary Note 2.2). With the GBD 2017–based results, vehicle electrification is still estimated to result in greater air quality-related health benefits than net climate benefits in the next decade.

Policy implications

China's EV sector has been considered a strategic emerging industry. The Ministry of Industry and Information Technology (MIIT) is responsible for policymaking for the automotive industry and has had an important role in designing incentives to expedite EV development. The core objectives of the ministry are to support the domestic EV industry and market, reduce fossil fuel consumption and mitigate GHG emissions. Improving air quality is absent from the policymaking of EV incentives, largely because a concrete linkage between the EV incentive programmes and the air quality and health benefits is not established. Our study can potentially bridge this gap. Even though GHG emissions mitigation is listed as a core objective, our study shows that the air quality and health benefits from EV deployment far exceed the climate benefits in China by 2030. The ministry announced in 2019 that the subsidies for EV purchases from the central government would be scheduled to phase out after 2020[30]. As EV adopters receive fewer monetary incentives than before, it is the time for policymakers to consider how to align environmental and industrial interests when formulating incentive policies on electrifying the transportation sector. The health benefits are estimated to be more significant for populous megacities, suggesting that EV incentive programmes should be regionally differentiated by considering local features. Municipal governments of megacities are advised to promote more progressive incentives locally in addition to national policies and guidelines, including using transportation measures and other subsidies. Notably, Beijing has capped the total number of new vehicle registrations to control the excessive vehicle growth, and the annual quota for EVs, as a fraction of the total cap, has increased from 25% in 2015 to 60% in 2019. The allocation of new vehicle license quotas in Beijing can be further increased to effectively facilitate higher electrification ratios in the future (for example, to approach Scenario EV-PTC). Low emission zones in core districts are also an option by providing EVs with exclusive driving privileges. Given the phase-out of initial purchase subsidies after 2020, the local governments can annually subsidize EV owners on the basis of health benefits embodied in the actual electric mileage. Our study can contribute to the methodology of evaluating the cost effectiveness of EV-supportive policies.

Methods

Fleet electrification scenarios. In this study, we selected the future year of 2030 for depicting the air quality and health impacts of EV development in China. Fleet electrification was expected to occur among various vehicle categories except for medium-duty trucks and heavy-duty trucks (MDTs and HDTs, respectively). Two general EV technologies, BEVs and PHEVs, were estimated for each vehicle category. To assess the exclusive benefits of EVs, we designed one scenario in which there was no EV penetration in China's vehicle fleets by 2030 (Scenario w/o EV). By contrast, Scenario EV was designed to project a plausible EV penetration pattern in China through 2030. Four additional scenarios were designed to reflect various fleet electrification levels because of potential variations in incentive policies, vehicle technology improvements and consumer preferences. Compared with Scenario EV, they are one less-favourable scenario (Scenario EV-LOW) and three more-favourable scenarios (Scenario EV-POL, that is, more supportive policies only; Scenario EV-POT, that is, more supportive policies and technological improvements; and Scenario EV-PTC, respectively). To examine the impacts of different electricity sources, we designed two electrification scenarios with extreme marginal charging electricity (that is, coal-fired power plants versus non-fossil power plants), Scenario EV-Coal and Scenario EV-Clean, which had consistent EV market shares with Scenario EV.

Under Scenario EV, we primarily applied the future projection for LDPVs in Wu et al.[4]. First, future provincial-level LDPV populations through 2030 were estimated using the Gompertz model, except for places where new registrations are stringently limited (for example, Beijing, Shanghai). Second, diversified propulsion and fuel systems, such as grid-independent hybrid electric vehicles (HEVs), PHEVs and BEVs, were projected to penetrate the LDPV fleet and reduce the fleet average fuel consumption levels to meet certain targets in the future (5.0 l per 100 km in 2020, 4.0 l per 100 km in 2025 and 3.2 l per 100 km in 2030[31]). Currently (for example, 2015 to 2020), BEVs are more favoured than PHEVs in many cities; for example, PHEV purchases in Beijing are subsidized by only the central government but not the municipal government. When governments adopt a more technology-neutral standpoint to design incentive policies after 2020, for example, by reducing purchase subsidies, the competitiveness of PHEVs and HEVs will increase. For example, China's annual sales of PHEVs increased by 118% from 2017 to 2018, higher than the growth (51%) of BEVs. We estimated that EVs could account for 38% of the total LDPV market share (18% for PHEVs and 20% for BEVs) and accumulate 27% of the total LDPV population in 2030 in China (Supplementary Table 4). Higher electrification levels in the three developed regions indicate that these areas could introduce more incentive policies and other local incentive policies (for example, more-stringent license and driving controls for ICEVs) than the rest of China. The electrified ratio was projected to be as high as 30% in the three developed regions.

We also considered that the actual electrified mileage per EV would be shorter than the annual vehicle kilometres travelled (VKT) per ICEV due to battery capacity limitations because the all-electric ranges (AERs) for both BEVs and PHEVs may not be sufficient for casual long-distance travels[28]. We developed utility factor functions for BEVs (AER of 300 km) and PHEVs (AER of 50 km) based on longitudinal travel surveys of approximately 500 vehicles in China (Supplementary Note 1). On the ensemble level, the annual average electrified VKT was estimated to be 93% for BEV300 and 71% for PHEV50 (that is, 29% of mileage completed in charge-sustaining mode), respectively, relative to ICEVs (12,000 km in 2030)[4].

For commercial vehicle fleets, the electrification trend is more influenced by government policies in China. In particular, EVs are encouraged and subsidized for use in public and municipal fleets such as transit buses, taxis and municipal vehicles (for example, postal and sanitation vehicles). For Scenario EV, this study considered that 70% of conventional vehicles in taxi and public bus fleets nationwide would be replaced by EVs, and the electrification rate in the three developed regions would reach 80% according to the 3 yr Clean Air Action Plan 2018–2020[20]. For other MDPV and HDPV categories, we assumed that the penetration rates would be equal to the penetration rate of public buses due to future policy uncertainties. For truck categories, we considered that 20% of LDTs would be replaced by EVs according to the recent government plans to promote the usage of EVs among urban logistics and municipal services. We did not consider fleet electrification for MDT and HDT categories by 2030 because they could be intensively operated on intercity highways and rural roads. Charging inconvenience and long mileage are major barriers for electrifying MDTs and HDTs. The same VKT levels for ICEV counterparts were assumed for commercial BEVs.

As for other electrification scenarios, we estimated the relative purchase intention of electrified LDPVs at different favourable levels regarding policy, technology and consumer preference. Details of these additional scenarios are available in Supplementary Note 2.1. In summary, the EV population share of total LDPVs was estimated to be 15% in the least-favourable Scenario EV-LOW (all three favourable levels declined by half); this reached 52% in the most-favourable Scenario EV-PTC (all three favourable levels doubled).

Emission inventory. A multisector emission inventory was applied to quantify the variation patterns of five major pollutants (primary $PM_{2.5}$, NO_x, SO_2, NMVOC and NH_3) in 2030. The method, data source and validation of emission inventory, including the historical year (2015) and future cases (2030), have been documented in previous papers[4,32–34].

For on-road vehicles, future emission factors were estimated according to vehicle classification, fuel type, emission standard level and environmental and driving conditions through 2030 by using the emission factor model of Beijing vehicle fleet (EMBEV) model. The EMBEV model uses a modelling approach consistent with the one adopted in the National Emissions Inventory Guidebook by the Ministry of Ecology and Environment (formerly Ministry of Environmental Protection) of China[4]. The China 6/VI emission standards were implemented in 2019 and are expected to significantly reduce on-road emission factors by adopting more advanced after-treatment technologies and in-use compliance programmes (for example, regulations on real driving emissions). Due to the lack of measurement data for China 6/VI vehicles for the time being, we estimated the future emission factors of air pollutants in the previous study[4] on the basis of international experiences[12] as well as the relative trends in emission limits. For example, China VI heavy-duty diesel vehicles would employ improved selective catalytic reduction systems to control NO_x emissions, which were estimated compared to the Euro VI and US 2010 stages and could reduce their NO_x emissions by 80% relative to China V. Total on-road emissions were calculated on the basis of municipality level with detailed vehicle population, annual mileage and emission factors, and the emissions data for current (2015) and future (2020, 2025 and 2030) years are presented in Supplementary Table 6. The 24 h diurnal profiles of on-road emissions were also estimated on the basis of the temporal dynamics derived by real-world traffic monitoring data[29]. The gridded on-road emissions were allocated according to not only the density of the road network but also other important adjustments (for example, average traffic volume, road speed and fleet mix that were averaged by road type and area) derived on the basis of real-world traffic datasets (Supplementary Note 3)[35]. In Scenario EV, avoided on-road emissions were calculated on the basis of emission factors of ICEV counterparts and electrified annual mileage, which were shifted to other upstream sectors (power plants, as discussed in the next paragraph) according to energy consumption from a WTW perspective.

The methodology used for emission inventory development in other sectors has been reported by a series of studies[32–34]. We referred to the 2030 New Policy scenario in Wang et al.[32], which was developed mainly on the basis of the 2030 PC[1] scenario in Wang et al.[33] and has incorporated recent policies. The New Policy scenario can help most cities in China control their annual $PM_{2.5}$ concentrations below the National Ambient Air Quality Standard limit of 35 $\mu g\,m^{-3}$ by 2030. For the power sector, the emission data for years 2015, 2020 and 2030 are summarized in Supplementary Table 7. A unit-based approach was used to calculate high-resolution emissions. The total proportion of electricity production from coal-fired power plants will decrease to below 50% nationwide, ranging from 33% to 62% according to the power grid region (each power grid region consists of several provinces[36]; Supplementary Fig. 15). Advanced end-of-pipe control technologies, for example, flue-gas desulfurization for SO_2, electrostatic precipitators or high-efficiency dust collectors for $PM_{2.5}$ and low NO_x burner plus selective catalytic reduction system would be fully utilized by 2030[33]. Notably, various dispatch principles and interregional power transmission may lead to different marginal electricity mixes for EV charging[23]. However, due to the lack of explicit dispatch and interregional transmission information, this study referred to the regional average generation as the marginal electricity mix for Scenario EV and Scenario w/o EV. Thus, for each power grid region, the total electricity load for charging vehicles was estimated to be satisfied by all the power units in proportion to their electricity generation. Next, a typical diurnal profile of EV charging load previously applied by Ke et al.[7] was used to allocate the hourly demand. We developed two sensitivity scenarios to test the air quality and health impacts of varying marginal electricity, which assumed two extreme cases using purely coal-fired power (Scenario EV-Coal) versus non-fossil power (Scenario EV-Clean). For other sectors in the emission inventory, the unit-based approach (similar to the power sector) was also applied for major industrial plants (for example, iron, steel and cement). Activity information was collected, including data on the geographical location, capacity, boiler type, starting year, annual running hours, fuel type, fuel quality, coal consumption per unit electricity supply and emission control technologies[37]. This study used the spatial allocation method based on population and economics (for example, gross domestic production) indicators for area sources (for example, residential and small industrial plants)[34].

Weather Research and Forecasting–Community Multiscale Air Quality model configuration. We established a one-way, triple-nesting method in the Weather Research and Forecasting (WRF) model and Community Multiscale Air Quality (CMAQ) v 5.0.1 model to simulate the meteorology and air pollutant concentrations for Scenario w/o EV and Scenario EV. Domain 1 at a grid resolution of 36 km × 36 km covers the Greater China region, including Mainland China and part of East Asia and Southeast Asia regions; domain 2 covers East China at a grid resolution of 12 km × 12 km; the innermost domains 3 to 5 target three developed regions in East China with a resolution of 4 km × 4 km. Consistent with previous studies[7,38,39], we selected WRF simulations for four representative months (January, May, August and November) as the meteorological input for the CMAQ simulations. We incorporated a two-dimensional volatility basis set (2D-VBS) technique in the CMAQ model to improve the SOA simulation because the default SOA chemistry used in the CMAQ v 5.0.1 significantly underestimated SOA concentrations in China[38]. Previous papers have illustrated the detailed model setup[7] and validation against field observation results[38,39]. In this study, we also calculated the population-weighted concentrations for each prefecture-level city in the three developed regions of East China. We referred to a predicted geospatial distribution of the population in China[40], which considered the projected effects from population growth, urban expansion and rural-to-urban migrants through 2030. For other scenarios reflecting different fleet electrification levels (Scenario EV-LOW, Scenario EV-POL, Scenario EV-POT and Scenario EV-PTC), we conducted air quality simulations for domain 1 at a resolution of 36 km × 36 km and for the JJJ region as a finer-scale case study at a resolution of 4 km × 4 km (Supplementary Note 2.1). For the two sensitivity scenarios testing various power generation mixes (that is, Scenario EV-Coal and Scenario EV-Clean), air quality simulations for the three regions at a resolution of 4 km × 4 km were conducted, respectively.

Health impact assessment. This study assessed premature deaths in China and the three developed regions that are attributable to ambient air pollution by considering the top five $PM_{2.5}$-associated causes of death (health endpoints, including chronic obstructive pulmonary disease, ischemic heart disease, lung cancer, stroke and lower respiratory infections) and O_3-associated respiratory issues (chronic obstructive pulmonary disease). The population attributable fraction (PAF)[41–44] was applied to estimate the premature deaths attributable to $PM_{2.5}$ and O_3 as follows:

$$\mathrm{PAF}_{i,j,k} = 1 - 1/\mathrm{RR}_{i,j,k} \quad (1)$$

$$\Delta Y = \sum_{i,j,k} \mathrm{PAF}_{i,j,k} \times \mathrm{Pop}_k \times Y_{0_{i,j}} \quad (2)$$

In equations (1) and (2), i, j and k denote the air pollutants (annual $PM_{2.5}$ and summer O_3), health endpoint and ground-level gridded cell, respectively. In equation (1), $\mathrm{PAF}_{i,j,k}$ was calculated on the basis of the relative risk ($\mathrm{RR}_{i,j,k}$) assuming the prevalence of exposure to air pollution in the population would be 100% (ref. [43]). Equation (2) was used to calculate the health impact (that is, premature deaths) attributable to air pollutant exposures; ΔY is an attributable case, that is, premature deaths under each scenario; Pop_k is the cell-gridded population adapted on the basis of Shen et al.[40]; $Y_{0_{i,j}}$ stands for the baseline mortality rates. This study used the results from the GBD project (http://ghdx.healthdata.org/gbd-results-tool) to estimate $Y_{0_{i,j}}$ related to long-term annual $PM_{2.5}$ and summer O_3 (average daily 8 h maximum in May and August) exposure. Detailed information about the key parameters for various health endpoints applied in this study is presented in Supplementary Table 10 and Supplementary Fig. 4.

Local cohort data[45] have recently become available for studying the relationship between human chronic health and ambient $PM_{2.5}$ concentration in China. Compared with cohort datasets collected in developed countries, this study extended the upper range of $PM_{2.5}$ exposure levels up to 84 μg m^{-3}. However, the exposure risk in low-concentration situations has not been well characterized due to data scarcity for the time being. Recently, Burnett et al.[46] constructed $PM_{2.5}$-mortality risk ratio functions for GEMM based on 41 cohort studies from 16 countries, including a recent cohort study in China[45]. The relative risk function used by the GEMM is as follows:

$$\mathrm{RR}_{i,j,k} = \exp\left\{\frac{\theta_j \log\left(\frac{C_{i,k}-C_{\mathrm{cf}}}{\alpha_j}+1\right)}{1+\exp\left\{-\frac{C_{i,k}-C_{\mathrm{cf}}-\mu_j}{\nu_j}\right\}}\right\} \quad (3)$$

where $C_{i,k}$ is the simulated $PM_{2.5}$ concentration under each scenario, C_{cf} is the theoretical minimum risk exposure level (2.4 μg m^{-3} in this study) and θ_j, α_j, μ_j and ν_j are the GEMM parameters.

In contrast to the GEMM that was developed on the basis of the cohorts only regarding outdoor air pollution, the GBD adopted the integrated exposure–response functions[47] incorporating risk information from ambient $PM_{2.5}$ pollution and other sources (for example, secondhand smoke, household air pollution from use of solid fuels and active smoking). Xue et al.[48] conducted a census-based epidemiological study of $PM_{2.5}$ in China and found that a census-based estimation better aligned with the GEMM results than the integrated exposure–response function results. We discussed the difference in estimates of avoided $PM_{2.5}$-related premature deaths by using different relative risk functions (that is, GEMM, GBD2017 and Yin et al.[45]; Supplementary Note 2.2).

Regarding summer O_3 pollution, there has never been a well-established local cohort study to develop the relationship between mortality and long-term O_3 exposure. The GEMM addresses only the health impacts of $PM_{2.5}$ exposure. Therefore, we applied relative risk data (1.06, 1.02–1.10) from the latest GBD version (GBD2017)[49]; these data were developed on the basis of multiple cohort studies worldwide.

We further used the VSL to quantify the benefits of mortality risk reductions in monetary terms for evaluating the efficacy of electrification in the three regions. The city-specific VSL values were calculated via equation (4) (Supplementary Table 11), where $\mathrm{VSL}_{\mathrm{baseline}}$ is the VSL in a baseline year (2000–2001) and MVSL is the adopted marginal VSL value (unit of US$100 per US$) related to the per capita disposable income ($\mathrm{INC}_{\mathrm{percap}}$) between target and baseline years[50–53]. The per capita disposable income for 2030 was extrapolated on the basis of historical data from official statistical data (see Supplementary Note 2.3 for detailed methods). Notably, the VSL values derived from different studies could vary significantly by one order of magnitude; this issue was also mentioned by Li et al.[54]. For comparison, we calculated the VSL results on the basis of the US EPA methodology[55] in Supplementary Note 2.3. These results were higher than the value calculated using local data in China. Considering that the local data are more specific, we opted to apply the locally investigated data.

$$\mathrm{VSL}_{2030} = \mathrm{VSL}_{\mathrm{baseline}} + (\mathrm{INC}_{\mathrm{percap\ 2030}} - \mathrm{INC}_{\mathrm{percap\ baseline}}) \times \mathrm{MVSL} \quad (4)$$

The GHG mitigation benefits in monetary terms were also analysed for comparison. We estimated the WTW GHG emissions by following the Greenhouse Gases, Regulated Emissions and Energy Use in Transportation (GREET) model version 2017 (http://greet.es.anl.gov/) methodology and applying important local data (for example, carbon intensity of local power mix)[16]. The social cost of GHG emissions in this study was assumed to be US$47 (in 2015 value) per metric ton CO_2 equivalent (tCO_2e) (refs. [56,57]) with a discount rate of 3%. For comparison, we also calculated the monetary benefits of GHG emission reduction by applying different social carbon costs (for example, US$33 and US$167 per tCO_2e for lower and higher estimates)[57]. The estimation of CO_2e (CO_2, CH_4 and N_2O are included) was based on global warming potential over a 100 yr time horizon published by IPCC Fifth Assessment Report[58].

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

Data availability

The data that support the findings of this study are available from the corresponding author upon request.

Code availability

The code that supports the findings of this study is available from the corresponding author upon request.

Received: 18 April 2019; Accepted: 4 September 2019;
Published online: 7 October 2019

References

1. Williams, J. H. et al. The technology path to deep greenhouse gas emissions cuts by 2050: the pivotal role of electricity. *Science* **335**, 53–59 (2012).
2. Melton, N., Axsen, J. & Sperling, D. Moving beyond alternative fuel hype to decarbonize transportation. *Nat. Energy* **1**, 16013 (2016).

3. *Global EV Outlook 2019: Scaling-Up the Transition to Electric Mobility* (IEA, 2019).
4. Wu, Y. et al. On-road vehicle emissions and their control in China: a review and outlook. *Sci. Total Environ.* **574**, 332–349 (2017).
5. Mock, P. & Yang, Z. *Driving Electrification: A Global Comparison of Fiscal Incentive Policy for Electric Vehicles* (ICCT, 2014).
6. China Association of Automobile Manufacturers: the annual sales of new energy vehicles exceeded 1.25 million in 2018. *D1EV* https://www.d1ev.com/news/shuju/85937 (2019).
7. Ke, W. et al. Assessing the future vehicle fleet electrification: the impacts on regional and urban air quality. *Environ. Sci. Technol.* **51**, 1007–1016 (2016).
8. Peng, W., Yang, J., Lu, X. & Mauzerall, D. L. Potential co-benefits of electrification for air quality, health, and CO_2 mitigation in 2030 China. *Appl. Energy* **218**, 511–519 (2018).
9. Soret, A., Guevara, M. & Baldasano, J. M. The potential impacts of electric vehicles on air quality in the urban areas of Barcelona and Madrid (Spain). *Atmos. Environ.* **99**, 51–63 (2014).
10. Petroff, A. These countries want to ditch gas and diesel cars. *CNN Business* https://money.cnn.com/2017/07/26/autos/countries-that-are-banning-gas-cars-for-electric/index.html (2017).
11. Jonson, J. E. et al. Impact of excess NO_x emissions from diesel cars on air quality, public health and eutrophication in Europe. *Environ. Res. Lett.* **12**, 094017 (2017).
12. Anenberg, S. C. et al. Impacts and mitigation of excess diesel-related NO_x emissions in 11 major vehicle markets. *Nature* **545**, 467–471 (2017).
13. Bernard, Y., German, J., Kentroti, A. & Muncrief, R. *Catching Defeat Devices: How Systematic Vehicle Testing Can Determine the Presence of Suspicious Emissions Control Strategies* (ICCT, 2019).
14. The European Parliament & the Council of the European Union Regulation (EU) 2019/631: Setting CO_2 emission performance standards for new passenger cars and for new light commercial vehicles, and repealing Regulations (EC) No 443/2009 and (EU) No 510/2011. *EUR-Lex* https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32019R0631 (2019).
15. Huo, H., Zhang, Q., Liu, F. & He, K. Climate and environmental effects of electric vehicles versus compressed natural gas vehicles in China: a life-cycle analysis at provincial level. *Environ. Sci. Technol.* **47**, 1711–1718 (2013).
16. Ke, W., Zhang, S., He, X., Wu, Y. & Hao, J. Well-to-wheels energy consumption and emissions of electric vehicles: mid-term implications from real-world features and air pollution control progress. *Appl. Energy* **188**, 367–377 (2017).
17. Thompson, T. M., King, C. W., Allen, D. T. & Webber, M. E. Air quality impacts of plug-in hybrid electric vehicles in Texas: evaluating three battery charging scenarios. *Environ. Res. Lett.* **6**, 24004–24015 (2011).
18. Schnell, J. L. et al. Air quality impacts from the electrification of light-duty passenger vehicles in the United States. *Atmos. Environ.* **208**, 95–102 (2019).
19. Tessum, C. W., Hill, J. D. & Marshall, J. D. Life cycle air quality impacts of conventional and alternative light-duty transportation in the United States. *Proc. Natl Acad. Sci. USA* **111**, 18490–18495 (2014).
20. *2018–2020 Three-Year Action Plan for Winning the Blue Sky War* Guofa No. 22 (State Council, 2018).
21. Li, K. et al. Anthropogenic drivers of 2013–2017 trends in summer surface ozone in China. *Proc. Natl Acad. Sci. USA* **116**, 422–427 (2019).
22. *China 2030: Building a Modern, Harmonious, and Creative Society* (World Bank & Development Research Center of the State Council, 2013).
23. Chen, X. et al. Impacts of fleet types and charging modes for electric vehicles on emissions under different penetrations of wind power. *Nat. Energy* **3**, 413–421 (2018).
24. Tong, D. et al. Targeted emission reductions from global super-polluting power plant units. *Nat. Sustain.* **1**, 59–68 (2018).
25. Peng, W. et al. Managing China's coal power plants to address multiple environmental objectives. *Nat. Sustain* **1**, 693–701 (2018).
26. Kempton, W. & Tomić, J. Vehicle-to-grid power implementation: from stabilizing the grid to supporting large-scale renewable energy. *J. Power Sources* **144**, 280–294 (2005).
27. Hall, D., Cui, H. & Lutsey, N. *Electric Vehicle Capitals of the World: What Markets Are Leading the Transition to Electric?* (ICCT, 2017).
28. He, X. et al. Individual trip chain distributions for passenger cars: implications for market acceptance of battery electric vehicles and energy consumption by plug-in hybrid electric vehicles. *Appl. Energy* **180**, 650–660 (2016).
29. Zhang, S. et al. Fine-grained vehicle emission management using intelligent transportation system data. *Environ. Pollut.* **241**, 1027–1037 (2018).
30. *China Announced 2019 Subsidies for New Energy Vehicles* (ICCT, 2019).
31. *China Manufacturing 2025 Key Areas of Technology Roadmap* (in Chinese) (Advisory Committee of National Manufacturing Power-Building Strategy, 2015).
32. Wang, S. et al. Target and measures to prevent and control ambient fine particle pollution in China (in Chinese). *Chin. J. Environ. Manag.* **7**, 37–43 (2015).
33. Wang, S. X. et al. Emission trends and mitigation options for air pollutants in East Asia. *Atmos. Chem. Phys.* **14**, 6571–6603 (2014).
34. Zhao, B. et al. Change in household fuels dominates the decrease in $PM_{2.5}$ exposure and premature mortality in China in 2005–2015. *Proc. Natl Acad. Sci. USA* **115**, 12401–12406 (2018).
35. Yang, D. et al. High-resolution mapping of vehicle emissions of atmospheric pollutants based on large-scale, real-world traffic datasets. *Atmos. Chem. Phys.* **19**, 8831–8843 (2019).
36. Shen, W., Han, W. & Wallington, T. J. Current and future greenhouse gas emissions associated with electricity generation in China: implications for electric vehicles. *Environ. Sci. Technol.* **48**, 7069–7075 (2014).
37. Wang, S. et al. Verification of anthropogenic emissions of China by satellite and ground observations. *Atmos. Environ.* **45**, 6347–6358 (2011).
38. Zhao, B. et al. Quantifying the effect of organic aerosol aging and intermediate-volatility emissions on regional-scale aerosol pollution in China. *Sci. Rep.* **6**, 28815 (2016).
39. Zhao, B. et al. Impact of national NO_x and SO_2 control policies on particulate matter pollution in China. *Atmos. Environ.* **77**, 453–463 (2013).
40. Shen, H. et al. Urbanization-induced population migration has reduced ambient $PM_{2.5}$ concentrations in China. *Sci. Adv.* **3**, e1700300 (2017).
41. Rockhill, B., Newman, B. & Weinberg, C. Use and misuse of population attributable fractions. *Am. J. Public Health* **88**, 15–19 (1998).
42. Flegal, K. M., Panagiotou, O. A. & Graubard, B. I. Estimating population attributable fractions to quantify the health burden of obesity. *Ann. Epidemiol.* **25**, 201–207 (2015).
43. Zheng, X. et al. Association between air pollutants and asthma emergency room visits and hospital admissions in time series studies: a systematic review and meta-analysis. *PLoS ONE* **10**, e0138146 (2015).
44. Ding, D., Xing, J., Wang, S., Liu, K. & Hao, J. Estimated contributions of emissions controls, meteorological factors, population growth, and changes in baseline mortality to reductions in ambient $PM_{2.5}$ and $PM_{2.5}$-related mortality in China, 2013–2017. *Environ. Health Perspect.* **127**, 067009 (2019).
45. Yin, P. et al. Long-term fine particulate matter exposure and nonaccidental and cause-specific mortality in a large national cohort of Chinese men. *Environ. Health Perspect.* **125**, 117002 (2017).
46. Burnett, R. T. et al. Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. *Proc. Natl Acad. Sci. USA* **115**, 9592–9597 (2018).
47. 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).
48. Xue, T. et al. Change in the number of $PM_{2.5}$-attributed deaths in China from 2000 to 2010: comparison between estimations from census-based epidemiology and pre-established exposure–response functions. *Environ. Int.* **129**, 430–437 (2019).
49. Stanaway, J. D. et al. Global, regional, and national comparative risk assessment of 84 behavioural, environmental and occupational, and metabolic risks or clusters of risks for 195 countries and territories, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017. *Lancet* **392**, 1923–1994 (2018).
50. Hammitt, J. K. & Graham, J. D. Willingness to pay for health protection: inadequate sensitivity to probability? *J. Risk Uncertain.* **18**, 33–62 (1999).
51. Kan, H. et al. Differentiating the effects of fine and coarse particles on daily mortality in Shanghai, China. *Environ. Int.* **33**, 376–384 (2007).
52. Deng, X. Economic costs of motor vehicle emissions in China: a case study. *Transp. Res. D.* **11**, 216–226 (2006).
53. Wang, H. & Mullahy, J. Willingness to pay for reducing fatal risk by improving air quality: a contingent valuation study in Chongqing, China. *Sci. Total Environ.* **367**, 50–57 (2006).
54. Li, M. et al. Air quality co-benefits of carbon pricing in China. *Nat. Clim. Change* **8**, 398–403 (2018).
55. *Guidelines for Preparing Economic Analyses* (EPA, 2014).
56. *Technical Support Document: Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866* (Interagency Working Group on Social Cost of Greenhouse Gases, US Government, 2016).
57. Revesz, R. et al. Best cost estimate of greenhouse gases. *Science* **357**, 655 (2017).
58. IPCC *Climate Change 2014: Synthesis Report* (eds Core Writing Team, Pachauri, R. K. & Meyer, L. A.) (IPCC, 2014).
59. Long, Y. Redefining Chinese city system with emerging new data. *Appl. Geogr.* **75**, 36–48 (2016).

Acknowledgements

We are grateful to the National Key Research and Development Program of China (grant no. 2017YFC0212100) and the National Natural Science Foundation of China (grant no. 91544222 and 21625701) for supporting this research. S.Z. was supported by the David R. Atkinson Center for a Sustainable Future while at Cornell University. X.H. is supported by the University of Michigan–Ford Alliance Project. K.M.Z. acknowledges his support from the National Science Foundation through grant no. 1605407.

Author contributions

X.L. and S.Z. contributed equally to this study. X.L., Y.W., S.Z. and J.H. conceived the research idea; X.L., S.W., J.X. and S.Z. prepared the emission inventory data; X.L. and J.X. conducted air quality modelling and health impact assessments; X.H. provided the individual travel pattern dataset and UF analytic method; X.L., Y.W. and S.Z. analysed the data; J.H., J.X. and S.W. provided valuable discussions; X.L., Y.W., K.M.Z. and S.Z. wrote the paper with contributions from all authors.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information is available for this paper at https://doi.org/10.1038/s41893-019-0398-8.

Correspondence and requests for materials should be addressed to Y.W.

nature research

Corresponding author(s): Ye Wu

Last updated by author(s): Sep 2, 2019

Reporting Summary

Nature Research wishes to improve the reproducibility of the work that we publish. This form provides structure for consistency and transparency in reporting. For further information on Nature Research policies, see Authors & Referees and the Editorial Policy Checklist.

Statistics

For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

n/a	Confirmed	
☐	☒	The exact sample size (*n*) for each experimental group/condition, given as a discrete number and unit of measurement
☐	☒	A statement on whether measurements were taken from distinct samples or whether the same sample was measured repeatedly
☐	☒	The statistical test(s) used AND whether they are one- or two-sided *Only common tests should be described solely by name; describe more complex techniques in the Methods section.*
☐	☒	A description of all covariates tested
☐	☒	A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons
☐	☒	A full description of the statistical parameters including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals)
☐	☒	For null hypothesis testing, the test statistic (e.g. *F*, *t*, *r*) with confidence intervals, effect sizes, degrees of freedom and *P* value noted *Give P values as exact values whenever suitable.*
☐	☒	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☐	☒	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☐	☒	Estimates of effect sizes (e.g. Cohen's *d*, Pearson's *r*), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	(1) Emission inventory: source is described in the Methods section of the manuscript and data is provided in the supplementary materials (2) Meteorological model WRF input data: NCEP (downloaded from https://rda.ucar.edu/datasets/ds083.2/ (DOI: 10.5065); https://rda.ucar.edu/datasets/ds351.0/ (DOI: 10.5065); http://rda.ucar.edu/datasets/ds461.0/ (DOI: 10.5065)) (3) Baseline mortality information: GBD Results Tool (downloaded from http://ghdx.healthdata.org/gbd-results-tool) (4) Population data: source is described in the Methods section of the manuscript (5) China map used in figures: map files were published on the website Beijing City Lab (Data 38, Spatial cities of China in 2015, https://www.beijingcitylab.com), of which the provincial map was published by Long, Y. (Tsinghua University, ylong@tsinghua.edu.cn).
Data analysis	(1) Weather research and forecasting (WRF v3.3) (2) Community Multi-scale Air Quality (version 5.0.1) model enhanced by the two-dimensional volatility basis set (2D-VBS) (3) Greenhouse gases, Regulated Emissions, and Energy use in Transportation Model (GREET) version 2017 (4) ArcGIS version 10.2

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors/reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Research guidelines for submitting code & software for further information.

Data

Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A list of figures that have associated raw data
- A description of any restrictions on data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☐ Behavioural & social sciences ☒ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

Ecological, evolutionary & environmental sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	This study assessed air quality and health impacts of electric vehicle development in China, based on atmospheric chemistry transport modeling. Field experiment was not included.
Research sample	Field experiment was not included in this study. Atmospheric chemistry transport modeling was applied to simulate the air quality impacts.
Sampling strategy	In addition to the national-scale analysis, three developed regions (the Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta regions) were considered. Four typical months with various weather conditions were used for air quality simulations, which have been verified in previous studies.
Data collection	Authors collected the data needed for air quality modeling and health impact assessment. The detailed informations were included in the Manuscript and Supplementary materials.
Timing and spatial scale	Timing scale: hourly output in air quality modeling; The analysis in this study was based on daily, monthly and annual average data according to the corresponding air quality standards. Spatial scale: China at a grid resolution of 36km; Three regions at a grid resolution of 4km.
Data exclusions	No data were excluded.
Reproducibility	The detailed informations about the integrated modeling approaches applied in this study were described in the Methods section of the Manuscript and Supplementary materials.
Randomization	This is not relevant in this study because experiment was not included.
Blinding	During data acquisiton and analysis, absolute blinding was achieved.

Did the study involve field work? ☐ Yes ☒ No

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study	
☐	☐	Antibodies
☐	☐	Eukaryotic cell lines
☐	☐	Palaeontology
☐	☐	Animals and other organisms
☐	☐	Human research participants
☐	☐	Clinical data

Methods

n/a	Involved in the study	
☐	☐	ChIP-seq
☐	☐	Flow cytometry
☐	☐	MRI-based neuroimaging

Antibodies

Antibodies used	*Describe all antibodies used in the study; as applicable, provide supplier name, catalog number, clone name, and lot number.*
Validation	*Describe the validation of each primary antibody for the species and application, noting any validation statements on the manufacturer's website, relevant citations, antibody profiles in online databases, or data provided in the manuscript.*

Eukaryotic cell lines

Policy information about cell lines

Cell line source(s)	*State the source of each cell line used.*
Authentication	*Describe the authentication procedures for each cell line used OR declare that none of the cell lines used were authenticated.*
Mycoplasma contamination	*Confirm that all cell lines tested negative for mycoplasma contamination OR describe the results of the testing for mycoplasma contamination OR declare that the cell lines were not tested for mycoplasma contamination.*
Commonly misidentified lines (See ICLAC register)	*Name any commonly misidentified cell lines used in the study and provide a rationale for their use.*

Palaeontology

Specimen provenance	*Provide provenance information for specimens and describe permits that were obtained for the work (including the name of the issuing authority, the date of issue, and any identifying information).*
Specimen deposition	*Indicate where the specimens have been deposited to permit free access by other researchers.*
Dating methods	*If new dates are provided, describe how they were obtained (e.g. collection, storage, sample pretreatment and measurement), where they were obtained (i.e. lab name), the calibration program and the protocol for quality assurance OR state that no new dates are provided.*

☐ Tick this box to confirm that the raw and calibrated dates are available in the paper or in Supplementary Information.

Animals and other organisms

Policy information about studies involving animals; ARRIVE guidelines recommended for reporting animal research

Laboratory animals	*For laboratory animals, report species, strain, sex and age OR state that the study did not involve laboratory animals.*
Wild animals	*Provide details on animals observed in or captured in the field; report species, sex and age where possible. Describe how animals were caught and transported and what happened to captive animals after the study (if killed, explain why and describe method; if released, say where and when) OR state that the study did not involve wild animals.*
Field-collected samples	*For laboratory work with field-collected samples, describe all relevant parameters such as housing, maintenance, temperature, photoperiod and end-of-experiment protocol OR state that the study did not involve samples collected from the field.*
Ethics oversight	*Identify the organization(s) that approved or provided guidance on the study protocol, OR state that no ethical approval or guidance was required and explain why not.*

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

Human research participants

Policy information about studies involving human research participants

Population characteristics	*Describe the covariate-relevant population characteristics of the human research participants (e.g. age, gender, genotypic information, past and current diagnosis and treatment categories). If you filled out the behavioural & social sciences study design questions and have nothing to add here, write "See above."*
Recruitment	*Describe how participants were recruited. Outline any potential self-selection bias or other biases that may be present and how these are likely to impact results.*
Ethics oversight	*Identify the organization(s) that approved the study protocol.*

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

Clinical data

Policy information about clinical studies

All manuscripts should comply with the ICMJE guidelines for publication of clinical research and a completed CONSORT checklist must be included with all submissions.

Clinical trial registration	*Provide the trial registration number from ClinicalTrials.gov or an equivalent agency.*
Study protocol	*Note where the full trial protocol can be accessed OR if not available, explain why.*
Data collection	*Describe the settings and locales of data collection, noting the time periods of recruitment and data collection.*

Outcomes	*Describe how you pre-defined primary and secondary outcome measures and how you assessed these measures.*

ChIP-seq

Data deposition

☐ Confirm that both raw and final processed data have been deposited in a public database such as GEO.

☐ Confirm that you have deposited or provided access to graph files (e.g. BED files) for the called peaks.

Data access links *May remain private before publication.*	*For "Initial submission" or "Revised version" documents, provide reviewer access links. For your "Final submission" document, provide a link to the deposited data.*
Files in database submission	*Provide a list of all files available in the database submission.*
Genome browser session (e.g. UCSC)	*Provide a link to an anonymized genome browser session for "Initial submission" and "Revised version" documents only, to enable peer review. Write "no longer applicable" for "Final submission" documents.*

Methodology

Replicates	*Describe the experimental replicates, specifying number, type and replicate agreement.*
Sequencing depth	*Describe the sequencing depth for each experiment, providing the total number of reads, uniquely mapped reads, length of reads and whether they were paired- or single-end.*
Antibodies	*Describe the antibodies used for the ChIP-seq experiments; as applicable, provide supplier name, catalog number, clone name, and lot number.*
Peak calling parameters	*Specify the command line program and parameters used for read mapping and peak calling, including the ChIP, control and index files used.*
Data quality	*Describe the methods used to ensure data quality in full detail, including how many peaks are at FDR 5% and above 5-fold enrichment.*
Software	*Describe the software used to collect and analyze the ChIP-seq data. For custom code that has been deposited into a community repository, provide accession details.*

Flow Cytometry

Plots

Confirm that:

☐ The axis labels state the marker and fluorochrome used (e.g. CD4-FITC).

☐ The axis scales are clearly visible. Include numbers along axes only for bottom left plot of group (a 'group' is an analysis of identical markers).

☐ All plots are contour plots with outliers or pseudocolor plots.

☐ A numerical value for number of cells or percentage (with statistics) is provided.

Methodology

Sample preparation	*Describe the sample preparation, detailing the biological source of the cells and any tissue processing steps used.*
Instrument	*Identify the instrument used for data collection, specifying make and model number.*
Software	*Describe the software used to collect and analyze the flow cytometry data. For custom code that has been deposited into a community repository, provide accession details.*
Cell population abundance	*Describe the abundance of the relevant cell populations within post-sort fractions, providing details on the purity of the samples and how it was determined.*
Gating strategy	*Describe the gating strategy used for all relevant experiments, specifying the preliminary FSC/SSC gates of the starting cell population, indicating where boundaries between "positive" and "negative" staining cell populations are defined.*

☐ Tick this box to confirm that a figure exemplifying the gating strategy is provided in the Supplementary Information.

Magnetic resonance imaging

Experimental design

Design type	*Indicate task or resting state; event-related or block design.*
Design specifications	*Specify the number of blocks, trials or experimental units per session and/or subject, and specify the length of each trial or block (if trials are blocked) and interval between trials.*
Behavioral performance measures	*State number and/or type of variables recorded (e.g. correct button press, response time) and what statistics were used to establish that the subjects were performing the task as expected (e.g. mean, range, and/or standard deviation across subjects).*

Acquisition

Imaging type(s)	*Specify: functional, structural, diffusion, perfusion.*
Field strength	*Specify in Tesla*
Sequence & imaging parameters	*Specify the pulse sequence type (gradient echo, spin echo, etc.), imaging type (EPI, spiral, etc.), field of view, matrix size, slice thickness, orientation and TE/TR/flip angle.*
Area of acquisition	*State whether a whole brain scan was used OR define the area of acquisition, describing how the region was determined.*

Diffusion MRI ☐ Used ☐ Not used

Preprocessing

Preprocessing software	*Provide detail on software version and revision number and on specific parameters (model/functions, brain extraction, segmentation, smoothing kernel size, etc.).*
Normalization	*If data were normalized/standardized, describe the approach(es): specify linear or non-linear and define image types used for transformation OR indicate that data were not normalized and explain rationale for lack of normalization.*
Normalization template	*Describe the template used for normalization/transformation, specifying subject space or group standardized space (e.g. original Talairach, MNI305, ICBM152) OR indicate that the data were not normalized.*
Noise and artifact removal	*Describe your procedure(s) for artifact and structured noise removal, specifying motion parameters, tissue signals and physiological signals (heart rate, respiration).*
Volume censoring	*Define your software and/or method and criteria for volume censoring, and state the extent of such censoring.*

Statistical modeling & inference

Model type and settings	*Specify type (mass univariate, multivariate, RSA, predictive, etc.) and describe essential details of the model at the first and second levels (e.g. fixed, random or mixed effects; drift or auto-correlation).*
Effect(s) tested	*Define precise effect in terms of the task or stimulus conditions instead of psychological concepts and indicate whether ANOVA or factorial designs were used.*

Specify type of analysis: ☐ Whole brain ☐ ROI-based ☐ Both

Statistic type for inference (See Eklund et al. 2016)	*Specify voxel-wise or cluster-wise and report all relevant parameters for cluster-wise methods.*
Correction	*Describe the type of correction and how it is obtained for multiple comparisons (e.g. FWE, FDR, permutation or Monte Carlo).*

Models & analysis

n/a	Involved in the study
☐	☐ Functional and/or effective connectivity
☐	☐ Graph analysis
☐	☐ Multivariate modeling or predictive analysis

Functional and/or effective connectivity	*Report the measures of dependence used and the model details (e.g. Pearson correlation, partial correlation, mutual information).*
Graph analysis	*Report the dependent variable and connectivity measure, specifying weighted graph or binarized graph, subject- or group-level, and the global and/or node summaries used (e.g. clustering coefficient, efficiency, etc.).*

Multivariate modeling and predictive analysis	*Specify independent variables, features extraction and dimension reduction, model, training and evaluation metrics.*