

# Air quality trade-offs of a rapid expansion of personal electric vehicles in China

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## Article

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1 **Air quality trade-offs of a rapid expansion of personal electric vehicles in China**

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11

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1 **Abstract**

2 In China, replacing gasoline cars with electric vehicles (EVs) is at the center of a strategy to  
3 reduce air pollution and CO<sub>2</sub> emissions from transportation. Previous estimates of the benefits  
4 of vehicle electrification quantified the impact of EV use on on-road and power generation  
5 emissions only, thereby neglecting gasoline production. This study presents the first “use-cycle”  
6 analysis of EVs in China, including changes in emissions from transportation, power generation,  
7 and oil refineries. We use the GEOS-Chem atmospheric chemistry transport model to quantify  
8 how each sector contributes to the net impacts of EV use on air pollution (PM<sub>2.5</sub> and ozone) in  
9 China. We find that the projected growth in EV usage by the end of 2020 results in ~1,900 (95%  
10 CI: 1,600–2,200) avoided premature mortalities annually and a 2.4 Mton decrease in CO<sub>2</sub>  
11 emissions. 70% of the total reduction in mortality is due to avoided refinery emissions. As  
12 refinery emissions become more tightly regulated, our work implies that the power generation  
13 sector must also become cleaner for EVs to remain beneficial.

## 1 **Introduction**

2 Outdoor air pollution in China causes over 900,000 premature mortalities each year<sup>1,2</sup>, and its  
3 reduction is a regulatory priority<sup>3</sup> for the country. In recent years, sector-specific policy strategies  
4 have been successful at reducing the emissions of air pollutants and their precursors<sup>4-8</sup>. In the  
5 transportation sector, EVs are considered a key element of the strategy to reduce air pollution-  
6 related health impacts. In 2015, an estimated ~25,000 premature mortalities in 2015<sup>12</sup> (~3% of  
7 the annual total from all sources<sup>13</sup>) were attributed to road emissions and ~49,000<sup>12</sup> (~6% of the  
8 annual total<sup>13</sup>) to the fuel processing sector.

9

10 The transition to EVs will also result in increased demand for electric power generation due to  
11 vehicle charging. Power generation emissions are already one of the largest contributors to  
12 outdoor air pollution in China, causing ~100,000 premature mortalities in 2015 (95% CI: 50,000–  
13 180,000) (11% of the yearly total)<sup>9,11,12</sup>. When evaluating the net impacts of the use of EVs on  
14 air pollution and CO<sub>2</sub> emissions, it is therefore necessary to quantify its effects on all three of  
15 these systems: transportation, fuel processing, and power generation. This study is the first to  
16 present such a vehicle “use-cycle” analysis to answer the question of whether replacing  
17 gasoline cars with EVs in China results in net air quality benefits.

18

19 Previous studies have been inconsistent in their estimates of the net impacts of EV use on  
20 emissions. While they estimated the impacts of fuel production for EVs (additional power  
21 generation for charging) on emissions<sup>17-23</sup> and on air quality<sup>24,25</sup>, they did not account for  
22 gasoline fuel production at oil refineries, thus likely underestimating the benefits of EV use. In  
23 addition, previous studies used average power grid emissions factors when estimating the  
24 impact of EV use on emissions from power generation, thereby neglecting power grid dynamics  
25 and their effects on the spatial and temporal distribution of emissions, which could result in an  
26 underestimate of the emissions penalty associated with EV use due to increased power

1 generation. Those studies which used detailed power grid modeling<sup>26,27</sup> did not consider the  
2 effect of EV use on emissions from oil refineries, despite their significance for air pollution<sup>12,28–30</sup>.

3

4 In contrast, this study presents a vehicle “use-cycle” analysis and develops a power grid-  
5 refineries-air quality model that is able to capture, at high spatial and temporal resolution, the  
6 impacts of EV deployment on air quality, including the role of power generation and refineries.

7 Unlike previous studies that focus on average nationwide estimates of the net impact of EVs, we  
8 also quantify the spatial distribution of their health impacts, which may have implications for  
9 environmental justice.

10

## 11 **1. Model and scenarios**

12 We estimate the impacts of EV use on the system that includes fuel production and fuel use: EV  
13 use requires additional power generation but has no associated on-road emissions. The use of  
14 conventional vehicles, by contrast, results in emissions at oil refineries, for gasoline production,  
15 and from the tailpipe when gasoline is burned.

16

17 We apply a “use-cycle” analysis to quantify the impact of EV use on emissions from power  
18 plants, refineries, and personal vehicles compared to a reference case. To calculate the impact  
19 of EV deployment on power plant emissions, we develop a unit-level, hourly power grid model.

20 In contrast to previous studies that use grid-average values, our approach accounts for unit-  
21 level emission rates, location, and operational conditions. To quantify reductions in on-road

22 emissions, we use province-level projections for EV demand, powertrain-specific energy

23 efficiency, and spatial and temporal emissions patterns in each province. We also estimate the

24 total volume of gasoline saved under the EV scenarios and estimate the corresponding

25 emissions at oil refining facilities following emissions intensities described by Zheng et al.<sup>29</sup> (see

26 Methods). We then use atmospheric chemistry-transport modeling to quantify the resulting

1 changes in air quality (considering PM<sub>2.5</sub> and ozone). The health impacts of these changes are  
2 computed using concentration-response functions derived from the epidemiological  
3 literature<sup>31,32</sup>.

4  
5 The impacts of EV deployment are calculated with respect to a reference case with no  
6 additional EVs on the road in 2020 compared to 2017, so that the difference in energy demand  
7 from passenger cars between 2020 and 2017 is met by new gasoline cars. Emissions from  
8 transportation and refineries in the reference case assume a fuel efficiency of new gasoline cars  
9 of 5 L/100 km, corresponding to the 2020 fuel-efficiency standard. This provides our baseline  
10 estimate for air quality. Our EV scenarios are based on an estimate of EV penetration by 2020  
11 in each province from the ECLIPSE dataset<sup>33</sup> and assume that EVs substitute  $1.8 \times 10^{11}$  vehicle-  
12 kilometers (VKM) of travel nationwide (3.5% of the total for passenger cars), requiring an  
13 additional 88.5 PJ of electricity generation. Details about the modeling approach are provided in  
14 the Methods section. All provinces are included in this analysis except Tibet and Hainan (Figure  
15 S1), which have largely separate power grids<sup>34</sup> and together represent less than 0.6% of the  
16 annual energy consumption<sup>35</sup>.

17  
18 As previous studies have demonstrated, charging speed and timing influence the emissions  
19 resulting from additional electricity demand<sup>26,27</sup>. We quantify this by considering four charging  
20 scenarios (Table 1). Compared to a “slow charging” case, fast charging has been shown to  
21 increase peak electricity demand and result in a disproportionate allocation of the EV load to  
22 fossil-fuel sources, thereby increasing total emissions<sup>27</sup>. Least-cost smart charging (“smart  
23 charging” hereafter) can reduce generation costs by mitigating demand peaks but may not  
24 reduce emissions. Finally, we simulate “e-smart charging”, in which carbon pricing is applied  
25 only to the EV charging load, thereby incentivizing the use of renewable electricity sources for

1 EV charging. Because the emissions response to the power demand from EVs changes with the  
 2 power grid, we simulate it with the 2017 power grid, and the projected 2022 power grid.

3

4 **Table 1. Charging scenarios considered in this study.** Total EV demand is the same for all charging scenarios.

Scenario	Maximum charging power for EVs	EV load allocation	Emissions pricing for EV load
Reference case	N/A	N/A	N/A
Slow charging	3 kW (home) 7 kW (working place, shopping center)	Instantaneous	None
Fast charging	60 kW	Instantaneous	None
Smart charging	3/7 kW	Within a 12-hour window starting when vehicle is connected	None
E-smart charging (smart charging with a carbon price for the EV load)	3/7 kW	Within a 12-hour window starting when vehicle is connected	CNY 200 per metric ton of CO <sub>2</sub>

5

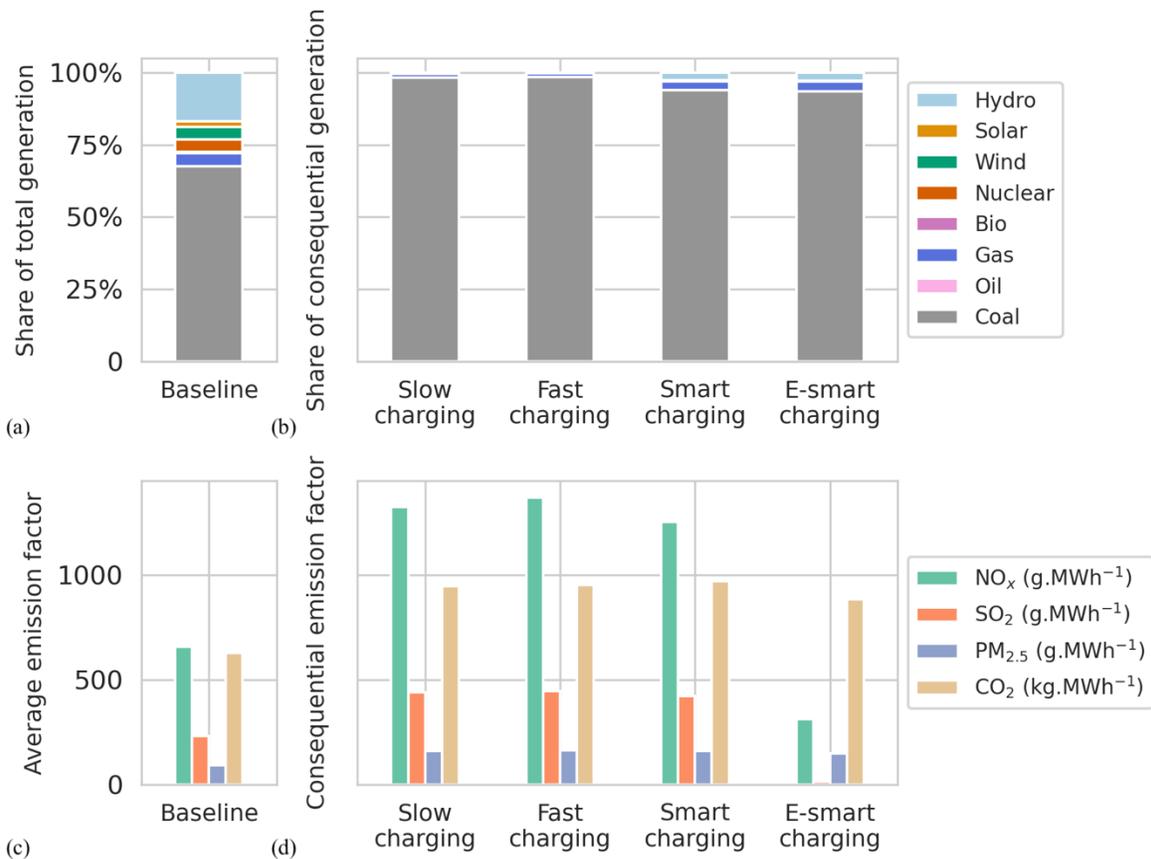
6 These four scenarios represent limiting cases, but serve to provide bounds to the real-world  
 7 impacts of EV deployment. Real-world deployment of EVs may combine slow and fast charging,  
 8 while smart and e-smart charging represent potential alternatives to the current load  
 9 management approach.

10

11 **2. Results**

12 **2.1. Impacts of EV deployment on emissions**

1 In the “slow charging” scenario, assuming displacement of 3.5% of the gasoline vehicle-  
 2 kilometers (VKM) by EVs (see Methods), we estimate power plant CO<sub>2</sub> emissions to increase by  
 3 23 Mton (0.6% of annual power emissions) while on-road CO<sub>2</sub> emissions decrease by 18 Mton  
 4 (2.7% of annual on-road emissions) and refinery CO<sub>2</sub> emissions decrease by 8 Mton (5% of the  
 5 annual emissions from refineries). This results in a net decrease in national annual emissions of  
 6 2.4 Mton CO<sub>2</sub>. The disproportionately large increase in power emissions is because the  
 7 generation capacity available to meet the EV load at the lowest cost given the base load (i.e.,  
 8 the consequential capacity) is composed mainly of coal-fired power plants (see Figure 1 (a) and  
 9 (b)). Under the EV scenarios, the power available for charging at the lowest cost comes from  
 10 coal sources and the overall energy mix becomes more reliant on coal. As a result, EV-related  
 11 electric demand is met by generation NO<sub>x</sub>, SO<sub>2</sub>, CO<sub>2</sub>, and PM<sub>2.5</sub> emission factors which are  
 12 101%, 90%, 51%, and 74% higher than the grid average, respectively (see Figure 1 (c) and (d)).



1 **Figure 1. Source of electricity generation by scenario and emission factor by source and scenario.** (a) Share  
2 of total generation by source in 2017. (b) Share of consequential generation by EV scenario. (c) Average grid  
3 emission factors. (d) Consequential emission factors by EV scenario. CO<sub>2</sub> emission factors are in kg.MWh<sup>-1</sup>, while the  
4 other emission factors are in g.MWh<sup>-1</sup>. NO<sub>x</sub> emissions are reported on an NO<sub>2</sub> mass basis.

5

6 In both the slow and fast charging scenarios, electric demand for EVs peaks during the early  
7 evenings. It coincides with the pre-existing daily peak in total electricity demand, thus resulting  
8 in relatively high emissions. Smart charging assumes that EV charging can take place at any  
9 point in a predefined 12-hour window, so that the demand can be fulfilled by cheaper,  
10 underused gas and hydropower outside of peak hours. As such, smart-charging can reduce  
11 emission intensities, although emissions intensities are still 41-74% greater than the grid  
12 average. Smart charging with a carbon price for the EV load (“e-smart charging”) further  
13 reduces NO<sub>x</sub> and SO<sub>2</sub> emissions to 54% and 95% lower than the power grid average emission  
14 factors, but PM<sub>2.5</sub> and CO<sub>2</sub> emissions intensities are still 55 and 37% higher than the grid  
15 average. This indicates that while e-smart charging does not completely divert the EV load from  
16 coal to renewable sources, it dispatches the EV load to cleaner coal-fired power plants than  
17 smart charging.

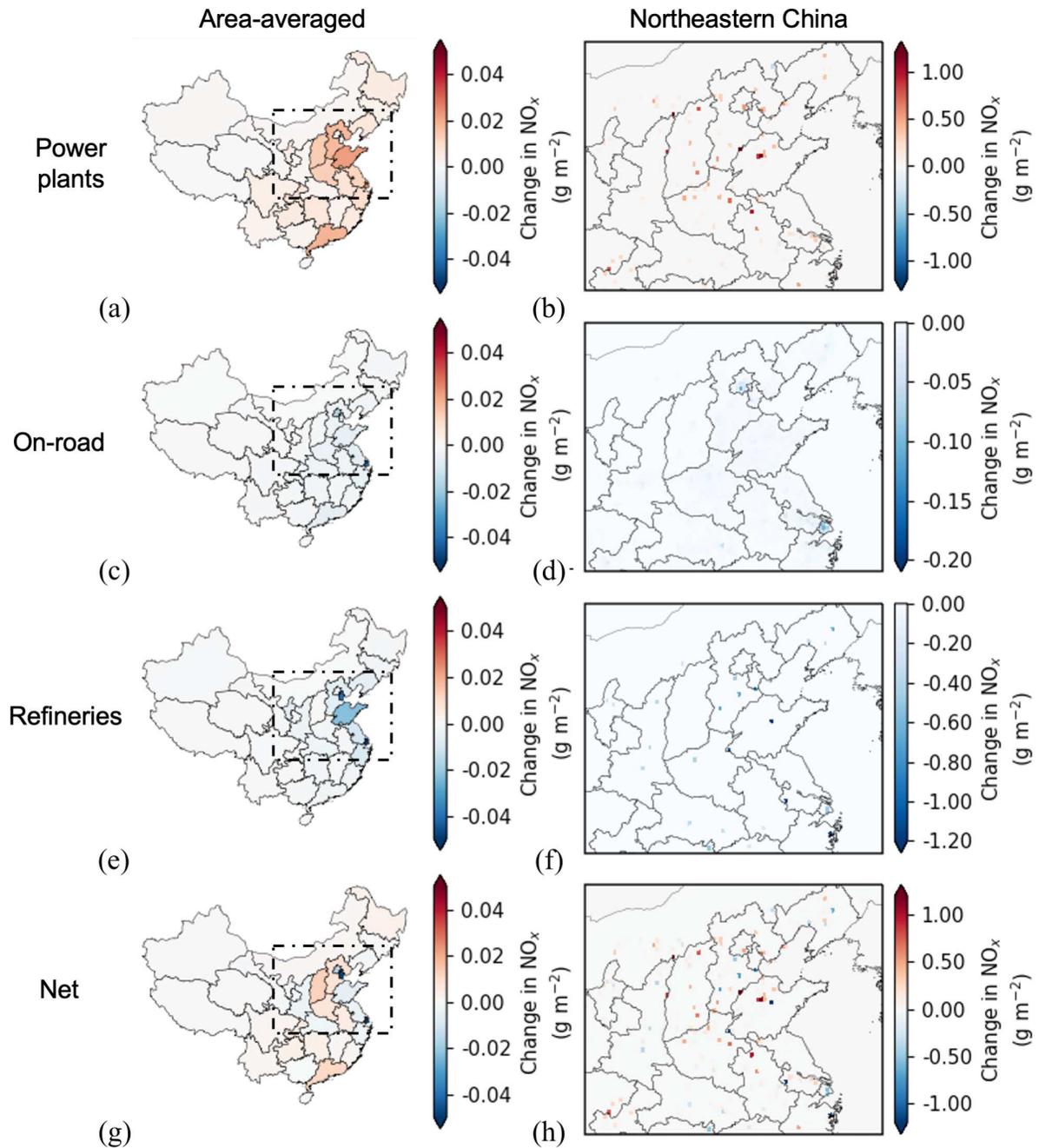
18

19 The spatial distribution of the increase in power generation NO<sub>x</sub> emissions in the slow charging  
20 scenario is shown in Figure 2 (a) and (b). Corresponding figures for SO<sub>2</sub> and PM<sub>2.5</sub> can be found  
21 in the Supplementary Information. EVs also contribute to a reduction in on-road emissions from  
22 personal vehicles and in refineries emissions, including CO, SO<sub>2</sub>, NO<sub>x</sub>, NH<sub>3</sub>, and volatile organic  
23 compounds (VOCs). Avoided car and refineries emissions for any given pollutant are assumed  
24 to have the same spatiotemporal distribution as car and refineries emissions of this pollutant in  
25 general, respectively.

26

1 In some provinces, total emissions are reduced by the national expansion of EVs (Figure 2 (e)  
2 and (f)). NO<sub>x</sub>, SO<sub>2</sub>, PM<sub>2.5</sub>, and CO<sub>2</sub> emissions decrease in Beijing (0.2%, 0.4%, 0.1%, and 0.3%  
3 respectively), but this is accompanied by increases from the nearby Hebei, Inner Mongolia, and  
4 Shanxi provinces. In total, 20 of the 29 provinces under consideration show increases in one or  
5 more of NO<sub>x</sub>, SO<sub>2</sub>, PM<sub>2.5</sub>, or CO<sub>2</sub> emissions, while 22 provinces show decreases in one or more  
6 of these pollutants.

7



1  
2 **Figure 2. Changes in NO<sub>x</sub> emissions** from (a) and (b) power plants, (c) and (d) on-road passenger vehicles, (e) and  
3 (f) refineries emission, and (g) and (h) all sources combined in the slow charging scenario. The left column shows  
4 regionally-averaged changes per unit area. The right column shows the spatial distribution over some of the most  
5 densely-populated areas, aggregated to the grid resolution (0.25°×0.25°).  
6

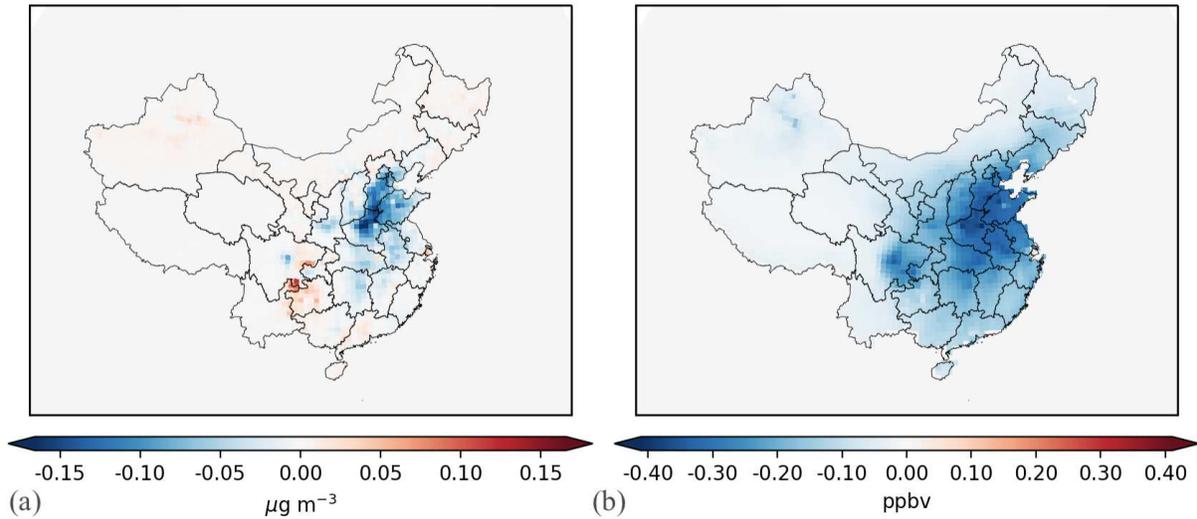
1 The spatial heterogeneity of emissions changes is due to the heterogeneity of demand, but also  
2 due to some provinces importing a large fraction of the electricity required to charge EVs. For  
3 example, Beijing and Tianjin are net importers of “EV electricity”: we estimate that they generate  
4 less than 10% of the electricity demand for EVs locally. Provinces such as Shanxi, Xinjiang, and  
5 Hebei are instead net exporters. The increase in power production in Shanxi, for example,  
6 corresponds to 1.7 times the increase in local demand. This reflects the growing reliance of the  
7 Chinese power grid on long-distance transmission<sup>36</sup>. Similarly, reductions in refineries emissions  
8 are heterogeneous, with 27% of the overall reductions expected in Shandong. The presence of  
9 refineries in a given province is a strong predictor of the net emissions benefits of the estimated  
10 EV deployment on emissions (Figure 2).

11

## 12 **2.2. Changes in air quality due to EV deployment**

13 Figure 3 shows the changes in air quality under the slow charging EV scenario compared to the  
14 baseline case where the equivalent demand for mobility is met by gasoline cars. The impacts  
15 shown are the net impacts considering the effect of replacing gasoline vehicles and refineries  
16 emissions as well as increases in electric power generation. Concentrations of both PM<sub>2.5</sub> and  
17 ozone are affected by changes in power plant, on-road, and refineries emissions. Compared to  
18 ozone, PM<sub>2.5</sub> is more sensitive to power plant emissions and is increased in central and  
19 southern provinces, while the national population-weighted exposure decreases. Ozone is more  
20 affected by the reductions in power and refineries emissions. It decreases in almost all regions  
21 and the national population-weighted exposure (annual mean maximum daily 8-hour average)  
22 falls by 0.21 ppbv.

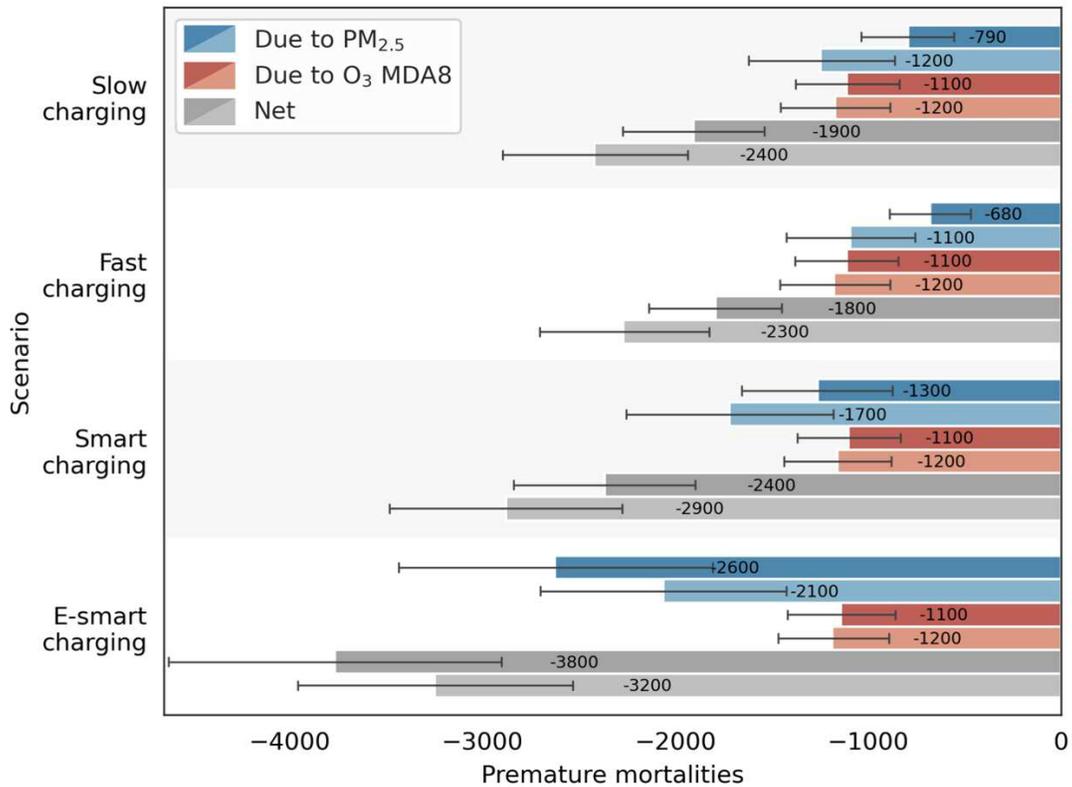
23



1 (a)  $\mu\text{g m}^{-3}$  (b) ppbv  
 2 **Figure 3. Changes in air quality under the slow charging scenario**, including displacement of conventional vehicles and reduced  
 3 refineries emissions. (a) Change in annual average  $\text{PM}_{2.5}$  concentrations. (b) Change in annual mean 8-hour maximum daily  
 4 average (MDA8) concentrations.

5  
 6 We propagate these emissions changes through to annual premature mortalities using  
 7 concentration-response function (details are in the Methods section). The total number of  
 8 premature mortalities estimated for each scenario relative to the baseline is summarized in  
 9 Figure 4.

10



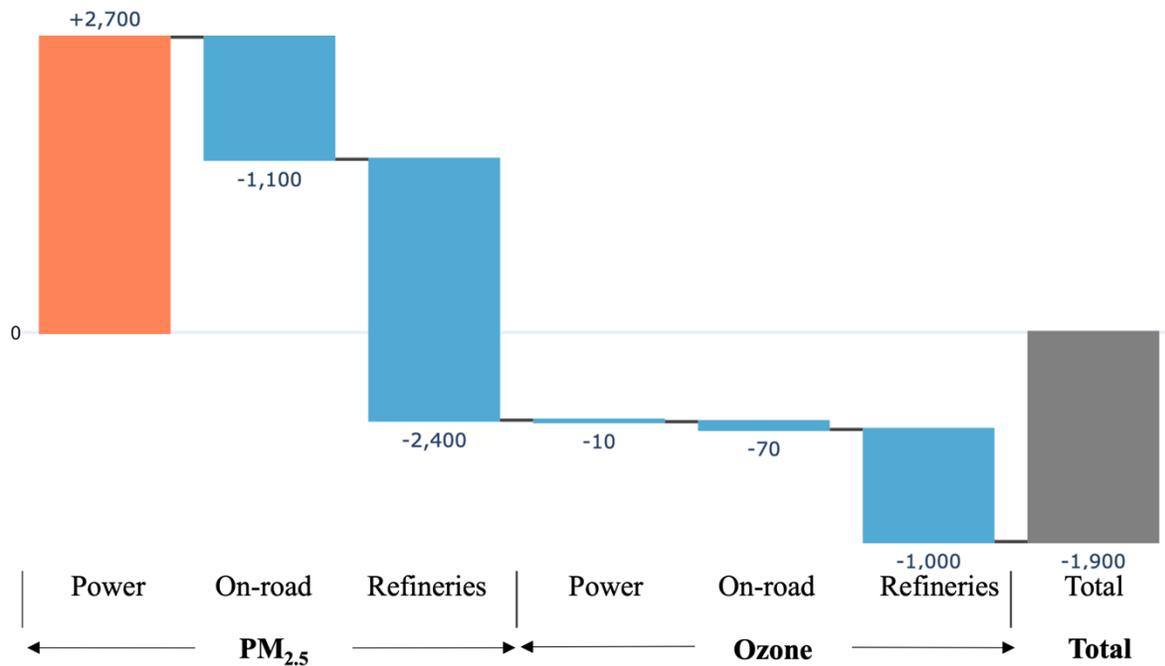
1  
2 **Figure 4. Number of annual premature mortalities in each EV scenario relative to the baseline case.** Results  
3 include benefits due to avoided emissions from gasoline vehicles and refineries. Results in dark colors (upper bar of  
4 each pair) are obtained with the 2017 (“current”) electric grid. Results in light colors (lower bars) are calculated using  
5 the projected electric grid for 2022. Error bars show the 95% confidence interval of the corresponding distribution of  
6 health impacts.

7  
8 Overall, despite increases in PM<sub>2.5</sub> concentrations in Central and Southern China, the  
9 deployment of EVs results in reduced premature mortalities in all scenarios. The slow charging  
10 scenario results in ~1,900 (95% confidence interval (CI): 1,600–2,200) avoided premature  
11 mortalities in 2017 relative to the baseline scenario (0.2% of premature mortalities associated  
12 with outdoor air pollution in China<sup>37</sup>). Fast charging results in the smallest improvements in air  
13 quality compared to the baseline (~1,800 (95% CI: 1,500 to 2,100) avoided premature  
14 mortalities), while smart charging yields 26% greater air quality benefits than slow charging  
15 compared to the baseline case (~2,400 (95% CI: 2,000–2,700) avoided premature deaths

1 compared to the baseline). Smart charging with carbon pricing (“e-smart charging”) results in  
2 the largest net air quality benefits relative to the baseline case (~3,800 (95% CI: 3,400–4,100)  
3 avoided premature deaths). This is because of a cleaner power grid response. This scenario  
4 also has the largest province-level benefits, with annual premature mortalities in Beijing  
5 decreasing by 140 (95% CI: 90-180). We also find 200 (95% CI: 160-240) prevented deaths in  
6 Chongqing and 70 (95% CI: 50-90) in Tianjin.

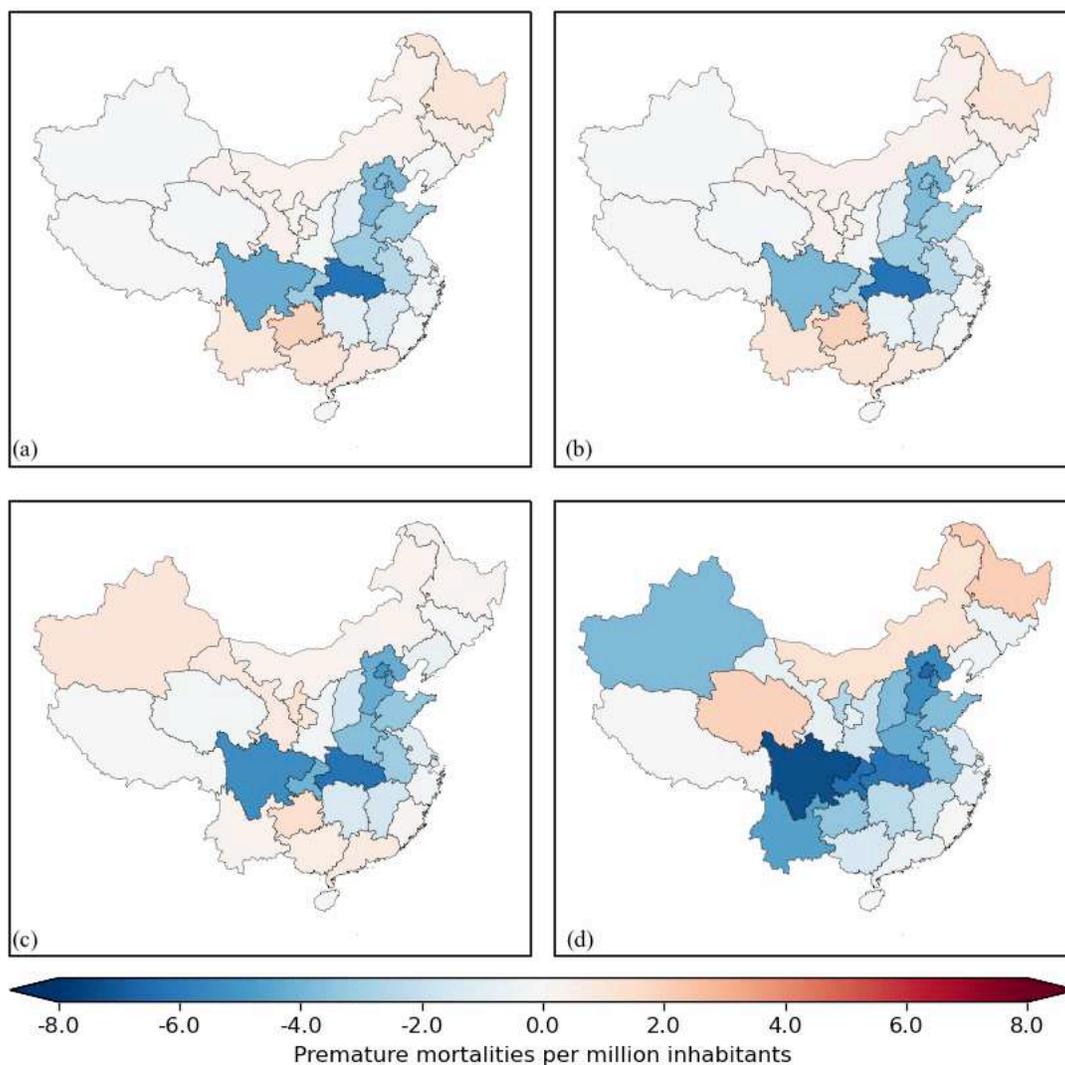
7  
8 To account for the rapid evolution of the Chinese power grid, we repeat our analysis with the  
9 projected power grid infrastructure and baseline demand for the year 2022<sup>38,39</sup> (Figure 4).  
10 Despite increases in the share of renewables in the total installed capacity, the majority of  
11 installed capacity in the 2022 grid is still coal (52% of the total installed capacity in 2022 vs. 56%  
12 in 2017). Total air quality benefits increase from ~1,900 (95%CI: 1,600–2,200) in the year-2017  
13 grid scenario to ~2,400 (95% CI: 2,100–2,700) avoided mortalities per year under the year-2022  
14 grid scenario with slow charging. However, CO<sub>2</sub> emissions only decrease by 4% due to the grid  
15 reliance on coal sources.

16  
17 Despite increases in power plant emissions resulting in increased concentrations of PM<sub>2.5</sub> in 20  
18 of the 29 provinces under consideration, we find that decreases in on-road and refinery  
19 emissions outweigh emissions increases from the power sector, resulting in net air quality  
20 benefits under all four EV scenarios. Figure 5 breaks down the net health impacts into the  
21 contribution attributable to changes in emissions from power plants, on-road, and refineries  
22 emissions. In the slow charging scenario, we find that reductions in emissions from refineries  
23 are the main driver of reduced exposure to ozone, contributing 93% of the total reduction in  
24 premature mortalities from ozone exposure and 69% of the reduction in PM<sub>2.5</sub> exposure.



**Figure 5. Contribution of changes in emissions in each sector to the calculated air quality impacts.**

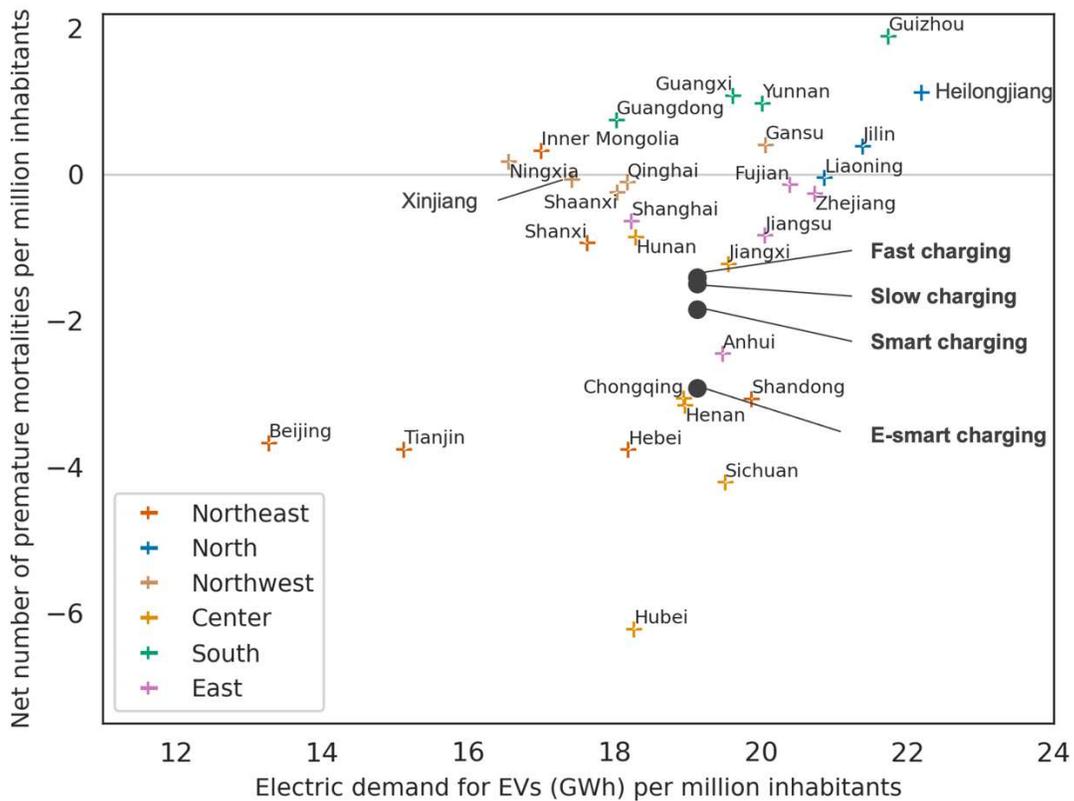
In all four scenarios, changes in premature mortalities are not evenly distributed among provinces. While central and northeastern China experience the largest decreases in air pollution-related premature mortalities in the EV scenarios, parts of eastern and southern China experience net increases in air pollution impacts (Figure 6). Under the slow and fast charging scenarios, 20 provinces have net decreases in premature mortalities, while nine have net increases. Under the e-smart charging scenario, all but four provinces have net decreases in air quality impacts; Heilongjiang, Inner Mongolia, Qinghai, and Fujian have increases in mortalities per capita under this scenario as more of the regional demand is dispatched to the less carbon-intensive – but still polluting - units in these regions. Results obtained with the 2022 power grid can be found in the Supplementary Information.



1  
 2 **Figure 6. Changes in the number of air pollution-related premature mortalities under different charging**  
 3 **scenarios. (a) Slow charging; (b) Fast charging; (c) Smart charging; (d) E-smart charging.**

4  
 5 The heterogeneity of net impacts is further illustrated for the slow charging scenario in Figure 7.  
 6 In Central and Northeastern China, EV penetration leads to a net decrease in mortality. In  
 7 Southern China, air pollution-related mortality increases with EV penetration. Most of the  
 8 country's major cities are in Northeastern and Eastern China, and the concentration of  
 9 population in these regions amplifies the benefits of reducing on-road emissions, while recent  
 10 efforts to develop long-distance transmissions have reduced the impact of power generation on  
 11 these regions' air quality<sup>36</sup>. Northeastern China also concentrates most of the oil refining

1 capacity, and therefore captures most of the benefits of reductions in refineries emissions (see  
 2 Supplementary Information). Overall, reductions in air quality-related premature mortalities and  
 3 electric demand for EVs in each province are only partially correlated ( $r^2=0.17$ ). This reflects the  
 4 fact that the air quality of a given province is influenced by emissions outside its borders, and  
 5 suggests that the introduction of EVs at the province-level alone might not be sufficient to  
 6 reduce air pollution locally while it may negatively impact neighboring provinces.



7  
 8 **Figure 7. Number of premature mortalities per capita vs electric demand from EVs per capita by province.**  
 9 Labeled crosses represent provinces under the slow charging scenario, while dots represent national average values  
 10 for each scenario. Crosses are colored by regional power grid (North, Northeast, Northwest, East, Center, and  
 11 South). The dashed line is the trend line. The squared correlation coefficient ( $r^2$ ) is 0.17.

12  
 13 These results are also sensitive to policy choices regarding vehicle availability and generation.  
 14 Lin and Wu<sup>40</sup> discuss the possibility of induced demand for EVs, i.e., that increased EV  
 15 production will increase car sales and total traffic rather than displacing gasoline vehicles. Such

1 induced demand could be driven by changing consumer behavior for EVs, e.g., in response to a  
2 lifting of existing vehicle licensing restrictions for EVs in cities such as Beijing and Shanghai, or  
3 to lower cost of ownership which would make EVs more affordable than gasoline cars. With  
4 substantial induced demand, the air quality benefits of EVs could be reduced or even reversed.  
5 We find that, if EV deployment does not displace gasoline vehicles and the reductions in  
6 refinery and on-road emissions are not included, then EV deployment would translate into  
7 ~2,700 (95% CI: 1,800–3,500) additional premature mortalities and 23 Mton of CO<sub>2</sub> emissions in  
8 the slow charging scenario.

9  
10 Our study suggests that the deployment of EVs in 2020 already has regional benefits to air  
11 quality in Central and Northeastern provinces compared to a baseline case with gasoline cars.  
12 However, net air quality benefits at the national scale could more than double if renewable  
13 sources were deployed to match the increase in electricity demand.

14

### 15 **3. Sensitivity analysis and discussion**

16 To account for uncertainties in the emission factors of power plants as reported in previous  
17 studies<sup>42,43</sup>, we repeat our analysis for the slow charging scenario with a uniform, 50% reduction  
18 in NO<sub>x</sub> emissions from power plants. The net benefit of the EV deployment on air quality in this  
19 case further increases by 42% (accounting for reduced on-road and refineries emissions). A  
20 similar scenario with a 50% reduction in SO<sub>2</sub> emissions increases the air quality benefits of the  
21 EV deployment by 11%.

22

23 In addition, we acknowledge that energy policies can have profound impacts on the outcomes. If  
24 installation of renewable capacity was increased such that new renewable sources exactly  
25 matched the EV load, the negative outcomes associated with increased power plant emissions  
26 could be avoided, and EVs would result in ~4,600 (95% CI: 3,700–5,400) avoided premature

1 mortalities due to improvements in air quality. Such a scenario would also imply a 26 Mton  
2 reduction in annual CO<sub>2</sub> emissions. These reductions may be underestimated, since we assume  
3 that the displaced gasoline cars in our baseline case meet the 2020 fuel economy standard of  
4 5L/100 km (compared to an average fuel economy of 5.8 L/100km in 2018<sup>41</sup>).

5  
6 Most studies on the impacts of EV deployment on emissions recommend the use of marginal  
7 emission rates from power plants<sup>27,46–49</sup>, consistent with this study's consequential approach.  
8 However, others argued that this approach is not well-suited for long-term studies<sup>50</sup> because  
9 new electricity generating units are built over time in response to projected increases in  
10 demand. To quantify the sensitivity of our results to the load allocation approach, we develop a  
11 sensitivity case where the EV load is allocated exclusively to recent generating capacity instead  
12 of consequential capacity (i.e. capacity built after 2017 and equipped with the most stringent  
13 emissions controls; see Methods). In this case, the modeled EV deployment results in ~3,800  
14 (95% CI: 3,100–4,500) avoided mortalities nationwide and a reduction of 13 Mton in CO<sub>2</sub>  
15 emissions. In addition, EV deployment is beneficial not only in Northeastern and Central  
16 provinces but also in Southern provinces (see Supplementary Information). This reinforces the  
17 fact that if the EV load in these provinces were matched with cleaner generation, the benefits  
18 associated with EV deployment would increase significantly.

19  
20 It has previously been reported that the GEOS-Chem model may overestimate the production of  
21 nitrate aerosol. We quantify the sensitivity of our results to nitrate aerosol by performing an  
22 additional set of simulations in which 25% of HNO<sub>3</sub> is removed at every time step<sup>44,45</sup>. This leads  
23 to a 27% increase in estimated net benefits of slow-charging EVs. In these cases, the spatial  
24 distribution of net air quality impacts is unchanged and EV deployment is more beneficial in  
25 Central and Northeastern China than in Eastern and Southern China. Results obtained with  
26 alternate concentration-response functions vary from ~1,400 (95% CI: 800–2,000) avoided

1 premature mortalities to ~2,300 (95% CI: 1,700–2,900) instead of ~1,900 (95% CI: 1,600–2,200)  
2 (detailed results from the sensitivity analyses are presented in the Supplementary Information).

3  
4 Additionally, the importance of a cleaner power grid will likely increase when recently  
5 announced restrictions on air pollutants' emissions from oil refining facilities<sup>28,30,51</sup> are fully  
6 implemented. As emissions from refineries decrease, so will the air quality benefits associated  
7 with displaced gasoline consumption from the deployment of EVs, which currently make up 70%  
8 of the total air quality benefits of EVs. Absent the benefits from reduced refineries emissions,  
9 the dominant driver of air quality changes under the EV scenarios is power plant emissions  
10 (Figure 7), which result in increases in ambient PM<sub>2.5</sub>. Therefore, to ensure that EVs continue to  
11 contribute to a reduction in air pollution, stricter emissions controls on power plants and further  
12 investment in renewable energy are needed.

13  
14 Our estimate for the CO<sub>2</sub> reductions due to the EV deployment, however, does not account for  
15 emissions associated with the production of EVs, in particular their battery. Battery  
16 manufacturing alone has been shown to make electric vehicle production 30% more GHG-  
17 intensive than gasoline vehicle production<sup>53</sup>, and including them would reduce the calculated  
18 benefit of EV deployment on CO<sub>2</sub> emissions. The impacts of battery manufacturing on air quality  
19 has not been explored in detail.

20  
21 Other benefits of EVs in China not accounted for are the reduced reliance on petroleum  
22 products imports, support for domestic manufacturing in the automotive sector, or mitigation of  
23 the urban heat island effect<sup>54</sup>. These factors can be considered in future cost-benefit analyses of  
24 EVs at the national level. This work does not account for potential changes in annual mileage  
25 driven when replacing gasoline cars with EVs. Finally, taking into account the fact that no single

1 charging mode is used for all EVs would better reflect actual on-road behavior and provide more  
2 granular insights on the real-world effect of EVs on air quality.

3

#### 4 **4. Conclusions**

5 This study presents the first “use-cycle” analysis of the impacts of EV use in China on air  
6 pollution and CO<sub>2</sub>. While previous studies only considered the impacts of EV deployment on  
7 road emissions and emissions from power generation, this study provides a use-cycle analysis  
8 that includes air quality impacts of both fuel production and fuel use for the EV and the  
9 conventional vehicle cases. We find that under the penetration of EVs in China in 2020, the  
10 effect of reduced on-road and refineries emissions outweighs that of increased power  
11 emissions. This results in ~1,900 (95% CI: 1,600–2,200) fewer early deaths per year, and  
12 decreases CO<sub>2</sub> emissions by 2.4 Mton per year for the current grid composition. 70% of the  
13 calculated decrease in premature mortalities under the EV scenario is from reduced emissions  
14 from oil refineries. Nonetheless, EV deployment has a detrimental impact on air quality in nine  
15 provinces, particularly in southern China. Least-cost smart charging is estimated to further  
16 increase the air quality improvements by 26% but has no significant impacts on CO<sub>2</sub> emissions  
17 (<1% difference with slow charging). Least-cost smart charging with a carbon price for the EV  
18 load is estimated to result in a net air quality benefit of ~3,800 (95% CI: 3,400–4,100) avoided  
19 premature mortalities per year and a 4.4 Mton decrease in annual CO<sub>2</sub> emissions.

20

21 Additionally, the air quality and climate benefits associated with EV deployment are increasing.  
22 If we assume a cleaner power grid (consistent with 2022 projections), the net reductions in  
23 mortality due to EVs would be increased by 26% in the slow charging scenario, while net CO<sub>2</sub>  
24 emissions would further reduce by 4% compared to 2017. Recently announced emissions  
25 controls on oil refining facilities would reduce the benefits of EV deployment on air quality and  
26 CO<sub>2</sub> emissions, unless cleaner power generation is deployed to match the EV load.

## 1 **5. Methods**

2 The following sections describe the methods used to obtain the results presented in the Main  
3 text. Section 5.1 presents the power grid model. Section 5.2 details how the demand for EV  
4 charging is estimated and allocated. The method to estimate reductions in on-road and  
5 refineries emissions is presented in Sections 5.3 and 5.4. Section 5.5 describes the air quality  
6 model, and Section 5.6 details this study's approach to health impacts analysis.

7

### 8 **5.1. Power grid model**

9 This study develops a model of the Chinese power grid for the years 2017 and 2022. It accounts  
10 for all of the installed power generation capacity at the plant-level and for the operational  
11 characteristics of each power plant. Fuel prices are defined by region, and we account for the  
12 ultra-high voltage transmission infrastructure to capture electricity imports and exports between  
13 regions. The electricity production of wind- and sun-powered generators is also constrained by  
14 hourly meteorology. Subsidy schemes for renewable sources such as feed-in tariffs are  
15 accounted for. The Supplementary Information has a detailed summary of all the sources that  
16 were used to construct the 2017 and 2022 models of the power grid.

17

18 For the 2022 grid model, projections for the installed capacities and base load demand are  
19 taken from Global Data Power and the Global Energy Monitor<sup>38,39</sup>. New capacity installed  
20 between 2017 and 2022 is assumed to be equipped with state-of-the-art, fully operating de-NO<sub>x</sub>  
21 and de-SO<sub>2</sub> devices and to possess latest-generation operational characteristics. The annual  
22 power demand from EVs by province is taken from GAINS v5a<sup>55</sup>, and the charging times are  
23 adapted from Chen et al.<sup>27</sup>.

24

25 To simulate the operation of the power grid and its response to the additional load from electric  
26 vehicles, we use an economic dispatch model. In the model, the electric demand is satisfied

1 through a cost minimization approach for each hour (unit commitment problem). This unit  
 2 commitment problem can be modeled as a linear optimization problem, where the objective is to  
 3 minimize the total cost of each additional unit of electricity generation. The algorithm calculates  
 4 the total cost of generation as the combination of the cost of electricity production and the cost  
 5 of transmission. Production costs are calculated as  $c_g$  (in CNY.MWh<sup>-1</sup>), multiplied by  $x_{g,t}$  the  
 6 total number of MWh to be produced by that generator during that hour. Transmissions costs  
 7 are calculated as the total number of MWh to be transmitted from the origin region  $o$  to the  
 8 destination region  $d$  ( $y_{o \rightarrow d}$  in MWh), multiplied by the cost of transmission for that line  $c_l$  in CNY  
 9 MWh<sup>-1</sup>. The objective function is therefore

$$10 \quad \min \sum_{g \in \mathcal{G}} \sum_{t=1}^T x_{g,t} c_g + \sum_{(o,d) \in \mathcal{L}} \sum_{t=1}^T y_{o \rightarrow d,t} c_l$$

11 where  $\mathcal{G}$  is the set of all generators,  $T$  the last hour considered, and  $\mathcal{L}$  the set of transmission  
 12 lines.

13  
 14 This optimization is performed subject to a series of constraints. Firstly, the power demand  $d_{p,t}$   
 15 at hour  $t$  in province  $p$  (part of set of provinces  $\mathcal{P}$ ) must be met by either local generation or net  
 16 imports from connected provinces, which translates to

$$17 \quad \forall p \in \mathcal{P}, \forall t \in \{1, \dots, T\}, d_{p,t} + \sum_{d \text{ s.t. } (p,d) \in \mathcal{L}} y_{p \rightarrow d,t} = \sum_{g \in \mathcal{G} \text{ s.t. } g \in p} x_{g,t} + \sum_{o \text{ s.t. } (o,p) \in \mathcal{L}} y_{o \rightarrow p,t}$$

18 where the left-hand side of the equation represents local demand and exports, while the right-  
 19 hand side represents local generation and imports.

20  
 21 Secondly, we apply minimum and maximum constraints for power generation in each plant. The  
 22 generation at each unit is constrained by that unit's maximum capacity  $X_{g,t}$ , which depends on  
 23 local, hourly meteorology in the case of wind and solar generators and on seasonal constraints  
 24 in the case of hydro:

1 
$$\forall g \in \mathcal{G}, \forall t \in \{1, \dots, T\}, 0 \leq x_{g,t} \leq X_{g,t}$$

2 Some units are required to produce at or above a certain level during certain periods of the  
3 year. From November to March, coal-fired combined heat and power (CHP) units in Northern  
4 provinces are required to produce a minimum of 60% of their nameplate capacity<sup>27</sup> to provide  
5 required heat output. In addition, nuclear power plants are constrained to produce at least 50%  
6 and no more than 90% of their nameplate capacity during any given hour, throughout the entire  
7 year.

8  
9 Finally, the transmission across each transmission line cannot exceed its maximum capacity  $Y$ :

10 
$$\forall (o, d) \in \mathcal{L}, \forall t \in \{1, \dots, T\}, 0 \leq y_{o \rightarrow d, t} \leq Y_{o \rightarrow d}$$

11 Under the smart charging and e-smart charging scenarios, the EV demand at any given hour is  
12 not required to be met within the same hour, and the grid operator may allocate the EV load  
13 during any of the following 12 hours. In the smart charging scenario, the allocation within that  
14 timeframe is set by cost only, while it includes both generation cost and carbon price of CNY  
15 200 per ton of CO<sub>2</sub> emitted<sup>56</sup> in the e-smart charging scenario. Although lower than the Social  
16 Cost of Carbon (\$50 in the US, or ~CNY 340 in 2020<sup>57</sup>), this value represents an ambitious  
17 medium-term estimate in China<sup>57,58</sup>. This leads to new variables in the optimization problem that  
18 represent the share of the hourly generation at each unit that is destined for EVs. The objective  
19 function is also modified to include the cost of CO<sub>2</sub> emissions from EV-related generation.

20  
21 This optimization problem is solved using the Julia language (Julia 1.1.0). We apply the  
22 optimization library JuMP 0.18.5<sup>59</sup> with the solver CPLEX 12.8<sup>60</sup>. The output of the power grid  
23 model is the quantity of electricity generated in MWh for each generator and each hour of the  
24 year (2017 or 2022). Combined with the emissions intensities derived from the references listed  
25 in Table 2, these results allow us to establish an hourly inventory of power plant CO<sub>2</sub>, NO<sub>x</sub>, SO<sub>2</sub>,  
26 and PM<sub>2.5</sub> emissions for the years 2017 and 2022. For each of the EV scenarios described in

1 the Main section above, hourly electricity demand for EV charging is added to the baseline  
2 demand and the model is resolved with the new total demand. This model is adapted from the  
3 US model developed by Jenn<sup>61</sup> and does not take into account ramping up and down  
4 constraints. Given that the Chinese power grid is dominated by coal, a relatively flexible  
5 source<sup>62</sup>, and that we constrain nuclear power plants in typical operational ranges, we do not  
6 expect that accounting for ramping constraints through a mixed-integer approach would  
7 significantly affect our results. Indeed, Henderson<sup>62</sup> suggests that recent coal-fired power plants  
8 are capable of changes of load exceeding 3% of their nameplate capacity per minute in  
9 operation. Given that our model operates at an hourly resolution, in-operation ramping  
10 constraints are not expected to modify our results. A remaining shortcoming of our approach is  
11 that we do not capture cold start-up times for coal power plants, which may last up to several  
12 hours<sup>62</sup>. Details about the model performance can be found in the Validation section of the  
13 Supplementary Information.

14

## 15 **5.2. Electric demand for EVs**

16 This section details how the EV demand was derived and allocated to specific hours of the  
17 years. Section 5.2.1 presents the derivation of the total energy used for personal vehicle  
18 transportation in the EV and counterfactual scenarios. Section 5.2.2 outlines how the electric  
19 demand for EVs was allocated to each hour of the year.

20

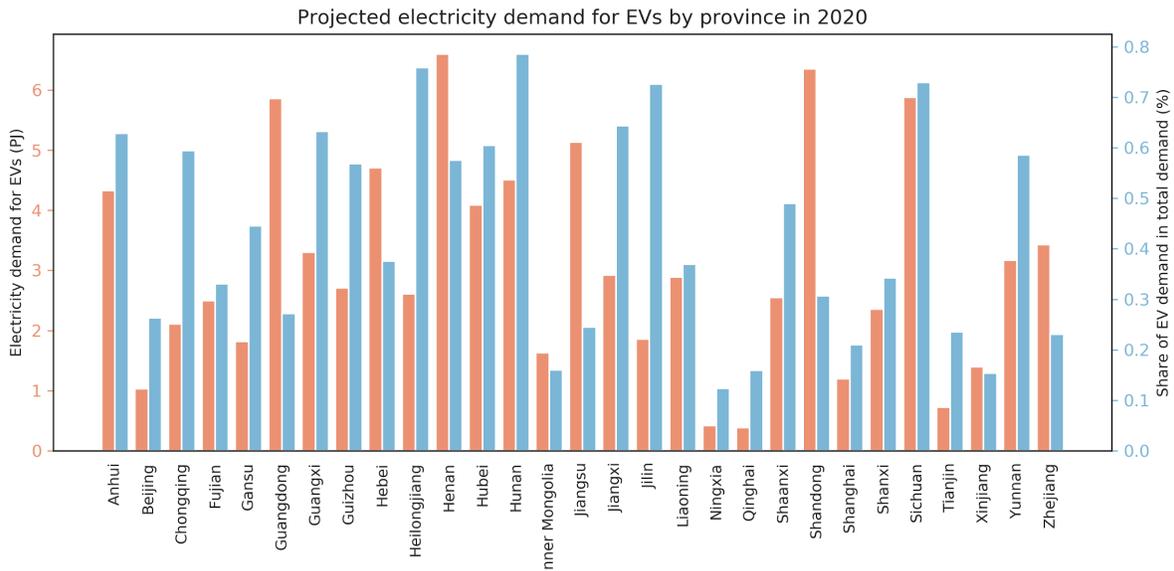
### 21 **5.2.1. Estimating total annual demand by province**

22 The annual power demand from EVs by province is taken from the GAINS China model  
23 (ECLIPSE CLE scenario v5a<sup>33</sup>) and totals 88.49 PJ for 2020. Projections for the EV demand are  
24 derived from the objectives formulated in the 12<sup>th</sup> Five-Year Plan that covers the period 2011-  
25 2015. This total represents 1.1% of the projected total energy demand for cars in 2020.

26 Assuming an efficiency of 14 kWh/100 km for EVs and 5 L/100km for gasoline cars, EVs will be

1 responsible for 3.5% of distance traveled in 2020 under this projection. They will also be  
 2 responsible for 0.38% of the total grid electrical energy demand in China, assuming no change  
 3 from 2017. The projected energy demand for EVs by province is shown in Figure 8.

4



5

6 Figure 8. Projected electricity demand for EVs by province in 2020 (red bars, left) and share of projected EV demand  
 7 in total province-level demand (blue bars, right).

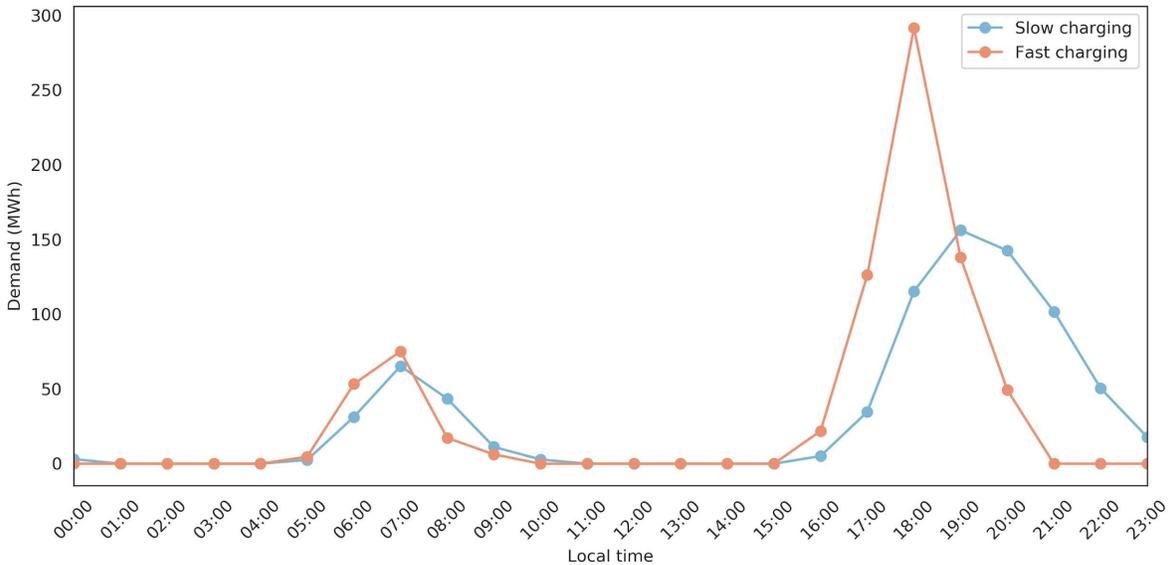
8

9 **5.2.2. Temporal profile of the EV demand for each scenario**

10 To allocate annual EV demand to individual hours of the year, we follow the approach  
 11 developed in Chen et al.<sup>27</sup>. The approach distinguishes demand patterns for weekdays from  
 12 demand patterns for weekends, and considers EV charging at home, at work, or at shopping  
 13 centers. In each category, each day is assumed to bear the same share of the annual EV load.  
 14 Hourly demand for EV charging on a typical weekday is represented in Figure 9 for the slow and  
 15 fast charging scenarios. During the week, three charging locations are considered: workplace  
 16 (7kW, in the mornings, making up 20% of the daily EV load), home (3kW, at night, representing  
 17 70% of the daily EV load) and shopping centers (7kW, at night, representing 10% of the daily  
 18 EV load). On weekends, we consider that half of the charging takes place at shopping centers,

1 and the other half at home. In the fast charging case, the charging rate at all locations is set at  
2 60 kW, a typical value for fast charging<sup>27</sup>.

3  
4 Despite the fact that all provinces operate under the same time zone, the timing of electricity  
5 demand varies between provinces<sup>27</sup>. To account for this profile, EV load is allocated to  
6 individual hours based on the apparent time zone at each of the provinces' centroid. This  
7 approach preserves the ratio of EV demand to general electric demand throughout the day<sup>27</sup>.  
8 The time difference between UTC time and the apparent time zone is defined as the longitude  
9 of the province centroid divided by 15 and rounded to the nearest integer. Finally, in all  
10 scenarios, we consider that the electricity required to charge one EV is 12.8 kWh (the average  
11 value used by Chen et al.<sup>27</sup>), and that each EV is fully charged once per day.



12  
13 Figure 9. Additional hourly demand due to EVs in Beijing in the slow charging scenario (blue) and fast charging  
14 scenario (red) on a weekday.

15  
16 The power dispatch model used in this study does not consider transmission constraints within  
17 provinces, so that the EV demand by province is not further spatially disaggregated. In the  
18 smart and e-smart charging cases, electric demand for EVs is input into the power grid model

1 as a constraint over 12-hour windows instead of 1-hour windows. This allows the EV load to be  
2 dispatched at any time within 12 hours of the first connection to the grid at the lowest cost.

3

### 4 **5.3. Emissions from gasoline vehicles**

5 To quantify the changes in road transportation emissions due to EV penetration, we use the  
6 average EV energy efficiency of all personal cars listed in the Ministry of Industry and  
7 Information Technology's New Energy Vehicle Product Catalog<sup>63</sup> (14 kWh/100 km) and a fuel  
8 economy for gasoline cars of 5 L/100 km, which corresponds to the 2020 standard for internal  
9 combustion engine personal cars<sup>64</sup>. This assumes that EVs replace new gasoline cars and  
10 allows us to estimate the gasoline consumption avoided in each province under the EV  
11 scenarios and the ratio of this quantity to the total gasoline consumption from passenger cars in  
12 each province (taken from the GAINS China model<sup>33</sup>). We use these province-level quantities  
13 and the share of passenger cars in road transportation emissions in each province estimated by  
14 the GAINS China model<sup>33</sup> to scale road transportation emissions of NO, CO, NH<sub>3</sub>, SO<sub>2</sub>, PM<sub>2.5</sub>  
15 and volatile organic compounds (VOCs) in the MIX inventory<sup>65</sup>. The avoided share of these  
16 pollutants' emissions in each province with EV deployment is shown in Table S1 in the  
17 Supplementary Information. Avoided emissions for any given pollutant are assumed to have the  
18 same spatio-temporal distribution as gasoline car emissions of this pollutant in general. The  
19 modified inventory serves as input to the GEOS-Chem chemistry-transport model in the EV  
20 scenarios. The relative changes in on-road emissions from gasoline cars in each province is  
21 summarized in the Supplementary Information.

22

### 23 **5.4. Emissions from refineries**

24 Changes in refineries emissions are derived from the total gasoline consumption avoided under  
25 the EV scenarios obtained with the method described in Section 5.3. and refineries emissions  
26 intensities from Zheng et al.<sup>29</sup>. Following recent data on imports of oil products, we assume that

1 95% of the gasoline consumed in China is refined in China; the remaining 5% is imported<sup>35</sup>. The  
2 air quality impacts from refineries emissions are estimated only for the share of gasoline fuel  
3 produced in China. To spatially allocate changes in emissions from oil refineries associated with  
4 the production of gasoline fuel, we use total annual output of gasoline by facility<sup>67,68</sup>. Changes in  
5 refineries emissions by province under the EV deployment scenarios are presented in the  
6 Supplementary Information.

7  
8 Emission factors associated with gasoline fuel production from Zheng et al<sup>29</sup> include nitrogen  
9 oxides (NO<sub>x</sub>), sulfur dioxide (SO<sub>2</sub>), fine particulate (PM<sub>2.5</sub>), and volatile organic compounds  
10 (VOCs). We further disaggregate VOCs emissions following Liu et al.<sup>66</sup>, who find that emissions  
11 from oil refineries are 45% alkanes, 5% alkenes, 10% aromatics, 20% OVOCs, and 20%  
12 halocarbons.

13  
14 Emission from oil refining facilities are constant across all EV charging scenarios, similar to  
15 emissions from road transportation. This means that we assume that EVs are driven the same  
16 distance and following the same temporal patterns regardless of the exact charging scenario.

## 18 **5.5. Air quality simulation**

19 Hourly emissions derived using the power grid model described above are fed into the GEOS-  
20 Chem model<sup>69-72</sup>. They are configured at run-time using the HEMCO module<sup>73</sup>. The model is  
21 driven by MERRA 2 meteorology<sup>74</sup> for the year 2017. Anthropogenic emissions in China and  
22 neighboring countries from sectors other than electricity generation as well as electricity  
23 generation in neighboring countries are provided by the MIX inventory for 2010<sup>72</sup>. MIX  
24 transportation emissions are modified in the EV scenarios to account for reduced on-road  
25 emissions in China. We run the model at a resolution of 0.5°×0.625° over East Asia  
26 (corresponding to about 320×200 grid cells, including 133×145 over China) with 47 vertical

1 layers up to an altitude of 80 km, 8 of which are at an altitude lower than 1 km. Boundary  
2 conditions are obtained at a resolution of  $2^{\circ} \times 2.5^{\circ}$  using a global simulation. All simulations are  
3 run over a 15-month period, including a 3-month “spin-up” period preceding the period of  
4 interest and excluded from the calculation of the results.  $PM_{2.5}$  and ozone concentrations at the  
5 lowest model level are assumed to correspond to “surface air”. We attribute the difference in  
6  $PM_{2.5}$  and ozone between each scenario and the reference case to the EV deployment.

7

## 8 **5.6. Health impacts analysis**

9 We relate changes in concentration of ozone and  $PM_{2.5}$  to changes in premature mortalities  
10 using concentration-response functions (CRF) from the epidemiological literature. In the case of  
11  $PM_{2.5}$ , the estimates reported in the Main Section were obtained using the Global Exposure  
12 Mortality Model<sup>31</sup> (GEMM). The GEMM expresses relative risk (RR) as a function of the  $PM_{2.5}$   
13 concentration in the form

$$14 \quad RR(z) = \exp [\theta \log(z/(\alpha + 1)) / \exp(-(z - \mu)/\nu)], \text{ where } z = \max(0, c - 2.4),$$

15 where  $c$  is the concentration of  $PM_{2.5}$  in  $\mu\text{g.m}^{-3}$  in each grid cell. The parameters  $\theta, \alpha, \mu, \nu$  are  
16 defined for each 5-year age bracket between 25 and 85 years of age. They are also endpoint-  
17 specific for the five  $PM_{2.5}$ -related health endpoints considered in this study (ischaemic heart  
18 disease, stroke, chronic obstructive pulmonary disease (COPD), lung cancer, and lower  
19 respiratory infection). We use the distributions provided in Burnett et al.<sup>31</sup> to generate 10,000  
20 independent samples of our estimated  $PM_{2.5}$ -related health impacts. We also implement two  
21 alternate CRFs to test the sensitivity of our results. We use the integrated exposure response  
22 function from the Global Burden of Disease 2015 study<sup>37</sup>, and apply a log-linear concentration-  
23 response function with parameters derived from a meta-analysis by Hoek et al.<sup>75</sup>. Results using  
24 alternate CRFs are shown in section S3.2.

25

1 For ozone, the results reported in the main text are obtained using a log-linear concentration-  
 2 response function with parameters derived from Turner et al.<sup>32</sup>. Turner et al. associated  
 3 exposure to 8-hour maximum ozone concentration to premature mortality from respiratory and  
 4 circulatory diseases (ICD-10 codes I00-I99 and J00-J99) using a two-pollutant model adjusted  
 5 for PM<sub>2.5</sub>. They found a central relative risk for circulatory diseases of 1.03 (95% CI: 1.01 to  
 6 1.05) and a central relative risk of 1.12 (95% CI: 1.08 to 1.16) for respiratory diseases. As for  
 7 PM<sub>2.5</sub>, we generate 10,000 samples for each of these parameters to estimate ozone-related  
 8 health impacts. The form of the log-linear function relating relative risk to the annual mean 8-  
 9 hour maximum daily average (MDA8) ozone concentrations is

$$RR(z) = \exp(\beta z), \text{ where } z = \max(0, c - 35),$$

11 with  $c$  the ozone MDA8 in ppb, and 35 ppbv the threshold suggested by Turner et al.<sup>32</sup>. Based  
 12 on the data reported in the original study, we estimate a central value of 0.00296 for  $\beta$  for  
 13 circulatory diseases, and 0.0113 for respiratory diseases.

14  
 15 The relative risk for each endpoint and age group is related to the number of premature  
 16 mortalities as

$$M_{d,a} = P_a \times B_{d,a} \times \frac{RR_{d,a} - 1}{RR_{d,a}}$$

18 where  $M_{d,a}$  is the number of premature mortalities from endpoint  $d$  and age group  $a$  in a given  
 19 grid cell,  $P_a$  the population in the age-group in that grid cell,  $B_{d,a}$  the baseline incidence, and  
 20  $RR_{d,a}$  the relative risk obtained using the CRFs described above<sup>76</sup>.

21  
 22 The spatial distribution of population in China in 2017 is taken from the Global Human  
 23 Settlement database maintained by the European Commission's Joint Research Center<sup>77</sup>, age  
 24 breakdown for 2017 is from WHO data<sup>78</sup>, and cause and age-specific incidence rates are  
 25 obtained from the Global Burden of Disease study 2017<sup>31,79</sup>.

1

2 The parameters for each of the concentration-response functions are considered independent

3 and treated as random variables with triangular distributions. Mode and 95% confidence

4 intervals are derived from the epidemiological studies.

5

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3 Karplus, and Mingwei Li for their help on this study and their valuable comments on the  
4 manuscript.

5

6 **Author Contributions**

7 GPC conceived the study and led the data acquisition and curation, methodology development,  
8 investigation, formal analysis, software development, validation, and visualization, with input  
9 from AJ regarding methodology, validation, visualization, and software development. SDE led  
10 the project administration and supervision, and contributed to the methodology, investigation,  
11 formal analysis, visualization and validation. FA and SRHB participated in the project  
12 administration and supervision, and provided feedback on the formal analysis and visualization.  
13 GPC wrote the original draft, and all authors contributed to review and editing.

14

15 **Competing Interest Declaration**

16 The authors declare no competing interests.

17

18 **Data and Code Availability Statement**

19 The code and datasets generated during and/or analyzed during the current study are available  
20 from the corresponding author.

21

22 **Additional Information**

23 Supplementary Information is available for this paper. Correspondence should be directed  
24 towards Guillaume Chossiere ([gchossie@mit.edu](mailto:gchossie@mit.edu)).

25

26

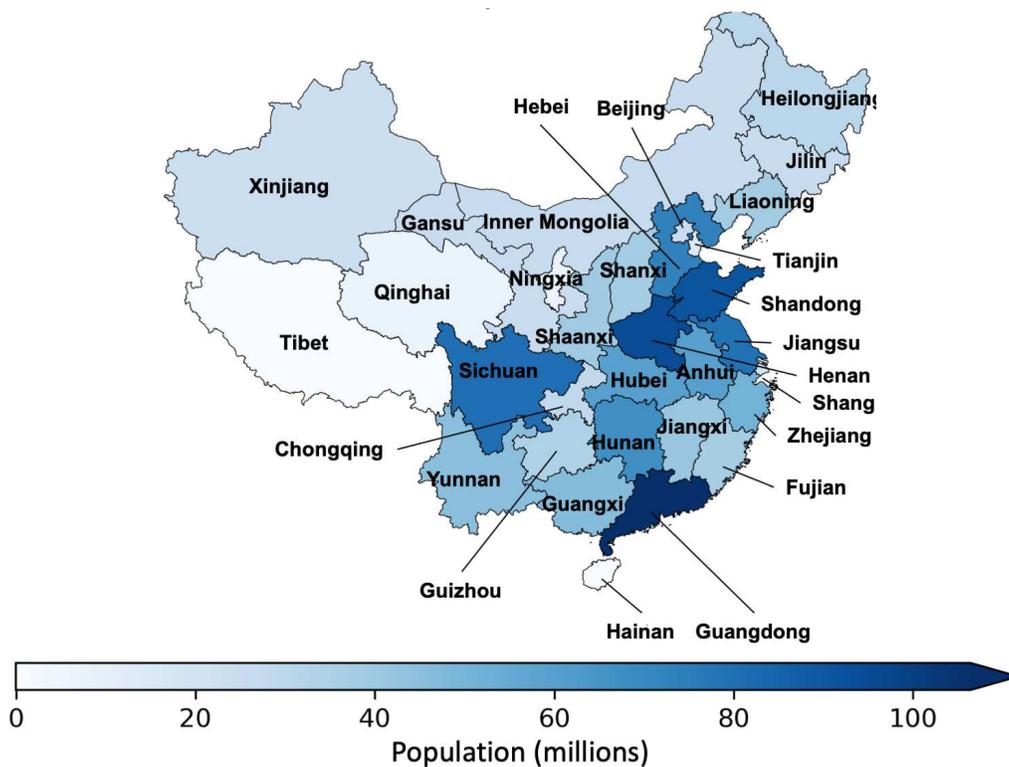
1 **Supplementary Information**

2

3 The following sections present the spatial distribution of population in China in Section S1,  
4 additional results with the 2017 power grid in Section S2, detailed results with the 2022 power  
5 grid in Section S3, additional scenarios run as sensitivity analysis in Section S4, and validation  
6 data for the power grid model and for the air quality model in Section S5.

7

8 **S1. Spatial distribution of population in China**



9

10 **Figure S1. Population by province.** Tibet and Hainan are excluded from this study.

11

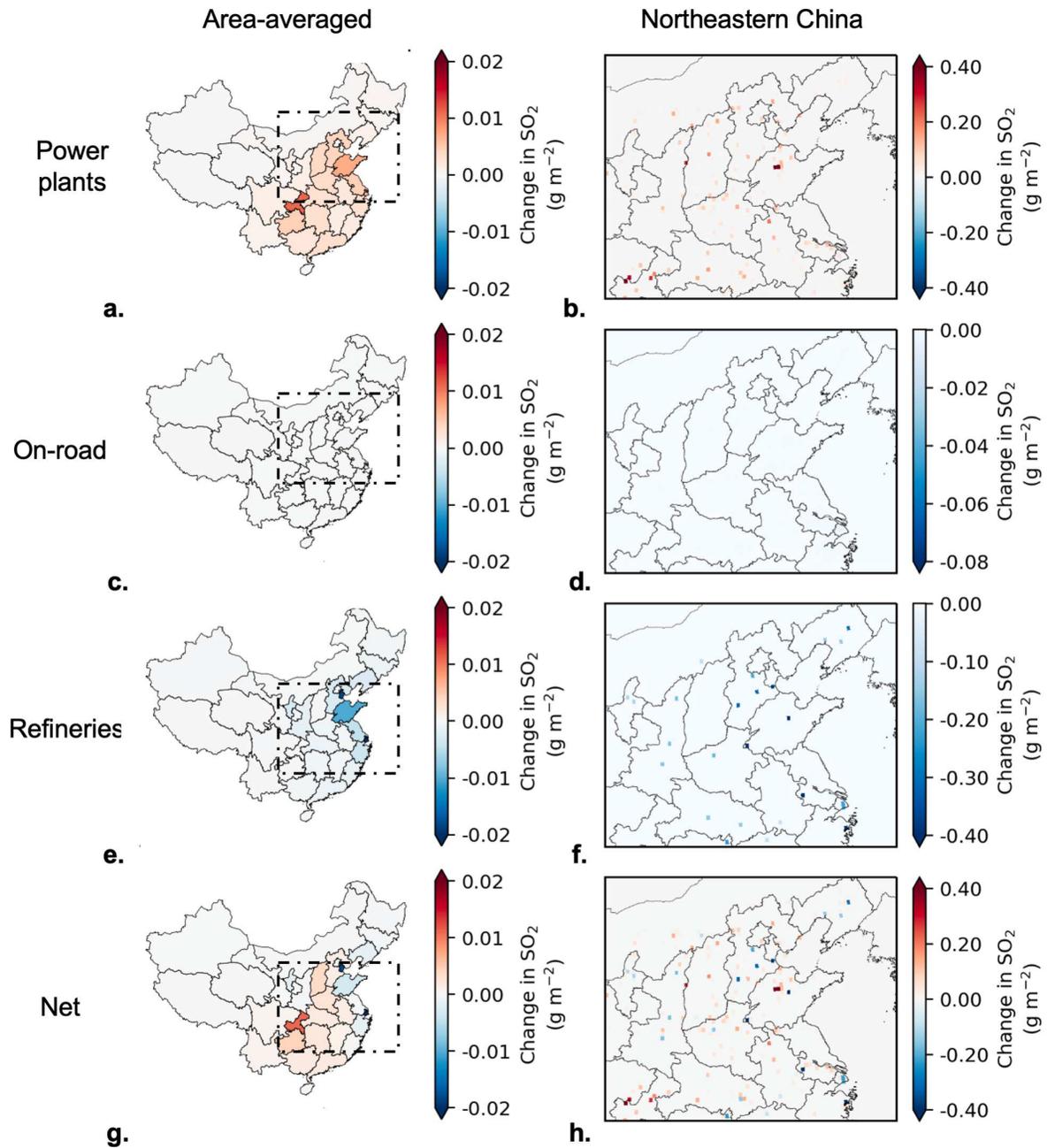
12 **S2. Additional results with the 2017 power grid**

13 This section presents the modeled changes in SO<sub>2</sub> and primary PM<sub>2.5</sub> emissions obtained with  
14 the 2017 power grid, as well as details about the reductions of on-road emissions that are  
15 modeled in the EV scenarios.

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7

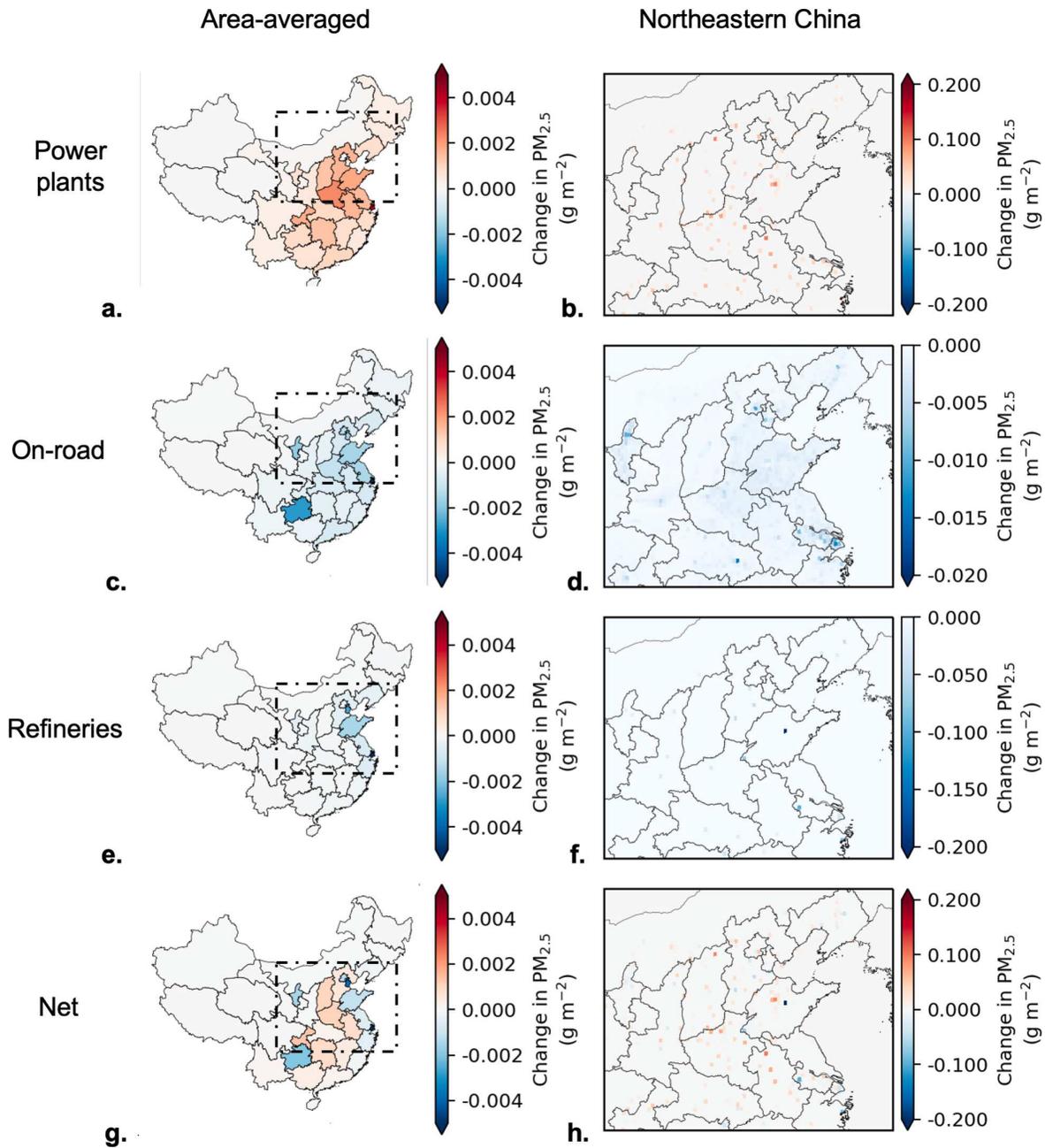
**S2.1. Change in SO<sub>2</sub> and PM<sub>2.5</sub> emissions under the slow charging scenario**

Similarly to the results summarized in Figure 4 of the main text, we present in Figures S2 and S3 below the changes in SO<sub>2</sub> and PM<sub>2.5</sub> emissions, respectively, under the slow charging scenario.



1  
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4  
5  
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**Figure S2. Changes in SO<sub>2</sub> emissions from power plants (top row, figures 4a and 4b), on-road passenger vehicles (middle row, 4c and 4d) and both sources combined (bottom row, 4e and 4f) in slow charging scenario. The left column shows changes averaged over each region. The right column shows the spatial distribution over some of the most densely-populated areas.**



1  
 2 **Figure S3. Changes in PM<sub>2.5</sub> emissions from power plants (top row, figures 4a and 4b), on-road passenger**  
 3 **vehicles (middle row, 4c and 4d) and both sources combined (bottom row, 4e and 4f) in slow charging**  
 4 **scenario. The left column shows changes averaged over each region. The right column shows the spatial distribution**  
 5 **over some of the most densely-populated areas.**

6

7 **S2.2. Share of road transportation emissions avoided by EV penetration**

1

Table S1. Percent share of road transportation emissions avoided by EV penetration

	CO	NH <sub>3</sub>	NO	PM <sub>2.5</sub>	SO <sub>2</sub>	VOC	CO <sub>2</sub>
Anhui	1.71	4.01	0.19	0.45	0.16	1.48	2.12
Beijing	0.86	1.04	0.32	0.33	0.02	0.88	0.94
Chongqing	1.70	3.94	0.19	0.44	0.18	1.53	2.20
Fujian	1.34	2.36	0.28	0.61	0.40	1.30	1.93
Gansu	2.03	5.27	0.22	0.50	0.17	2.04	2.30
Guangdong	1.13	2.06	0.34	0.53	0.37	1.06	1.56
Guangxi	1.44	2.70	0.25	0.55	0.23	1.29	2.27
Guizhou	2.79	6.41	0.36	8.59	0.36	2.65	3.90
Hebei	1.35	2.94	0.17	0.36	0.11	1.11	1.61
Heilongjiang	1.96	5.39	0.21	0.51	0.19	1.80	2.60
Henan	1.63	3.67	0.20	0.45	0.16	1.43	2.16
Hubei	1.70	3.42	0.25	0.56	0.23	1.55	2.48
Hunan	1.86	3.80	0.28	0.60	0.23	1.71	2.43
Inner Mongolia	1.16	2.87	0.13	0.31	0.12	1.03	1.58
Jiangsu	1.02	1.86	0.20	0.42	0.23	0.98	1.47
Jiangxi	1.32	2.60	0.20	0.46	0.23	1.23	1.98
Jilin	1.33	3.36	0.21	0.49	0.21	1.35	2.10
Liaoning	1.36	3.08	0.19	0.44	0.18	1.30	1.74
Ningxia	1.22	2.76	0.15	3.59	0.14	1.11	1.67
Qinghai	2.07	5.79	0.23	5.55	0.21	1.99	2.72
Shaanxi	1.36	3.11	0.18	0.43	0.20	1.31	1.97
Shandong	0.94	2.21	0.18	0.38	0.16	1.01	1.46
Shanghai	1.46	1.73	0.44	0.61	0.45	1.49	1.25
Shanxi	1.07	2.75	0.12	0.30	0.13	1.02	1.47
Sichuan	1.96	4.09	0.30	0.72	0.40	1.94	2.92
Tianjin	0.94	1.72	0.20	0.36	0.14	0.89	1.17
Xinjiang	0.99	2.87	0.16	0.36	0.18	0.96	1.81
Yunnan	1.18	3.26	0.27	0.63	0.35	1.20	2.46
Zhejiang	1.05	1.87	0.25	0.48	0.30	1.06	1.32

2

3

## 1 S2.3. Refineries emissions avoided by EV penetration

2 Table S2. Refineries emissions avoided by EV penetration

	GHG emissions (kg)	VOC emissions (kg)	NO <sub>x</sub> emissions (kg)	SO <sub>2</sub> emissions (kg)	PM <sub>2.5</sub> emissions (kg)
Anhui	5.313521e+07	5.942754e+04	1.252639e+05	5.709705e+04	8156.721280
Beijing	1.138612e+08	1.273447e+05	2.684227e+05	1.223508e+05	17478.688456
Fujian	1.290427e+08	1.443240e+05	3.042124e+05	1.386643e+05	19809.180251
Gansu	1.745871e+08	1.952619e+05	4.115815e+05	1.876046e+05	26800.655633
Guangdong	5.920781e+08	6.621926e+05	1.395798e+06	6.362243e+05	90889.179973
Guangxi	1.821779e+08	2.037516e+05	4.294763e+05	1.957613e+05	27965.901530
Hainan	8.349819e+07	9.338614e+04	1.968433e+05	8.972393e+04	12817.704868
Hebei	3.491743e+08	3.905238e+05	8.231630e+05	3.752092e+05	53601.311266
Heilongjiang	2.049501e+08	2.292205e+05	4.831609e+05	2.202315e+05	31461.639222
Henan	1.062704e+08	1.188551e+05	2.505279e+05	1.141941e+05	16313.442559
Hubei	1.821779e+08	2.037516e+05	4.294763e+05	1.957613e+05	27965.901530
Hunan	1.442241e+08	1.613033e+05	3.400021e+05	1.549777e+05	22139.672045
Inner Mongolia	5.313521e+07	5.942754e+04	1.252639e+05	5.709705e+04	8156.721280
Jiangsu	4.099002e+08	4.584410e+05	9.663218e+05	4.404629e+05	62923.278443
Jiangxi	5.313521e+07	5.942754e+04	1.252639e+05	5.709705e+04	8156.721280
Jilin	1.366334e+08	1.528137e+05	3.221073e+05	1.468210e+05	20974.426148
Liaoning	9.564338e+08	1.069696e+06	2.254751e+06	1.027747e+06	146820.983034
Ningxia	1.290427e+08	1.443240e+05	3.042124e+05	1.386643e+05	19809.180251
Qinghai	1.518149e+07	1.697930e+04	3.578970e+04	1.631344e+04	2330.491794
Shaanxi	2.808576e+08	3.141170e+05	6.621094e+05	3.017987e+05	43114.098193
Shandong	2.026729e+09	2.266736e+06	4.777924e+06	2.177845e+06	311120.654524
Shanghai	2.656761e+08	2.971377e+05	6.263197e+05	2.854852e+05	40783.606398
Sichuan	1.290427e+08	1.443240e+05	3.042124e+05	1.386643e+05	19809.180251
Tianjin	1.973594e+08	2.207309e+05	4.652660e+05	2.120748e+05	30296.393324
Xinjiang	2.808576e+08	3.141170e+05	6.621094e+05	3.017987e+05	43114.098193
Zhejiang	3.567650e+08	3.990135e+05	8.410578e+05	3.833659e+05	54766.557163

3

## 1 S2.4. Detailed sources for the power grid model

2 Table S3. Sources used to build the power grid model and specify the available capacity and characteristics in 2017  
3 and 2022.

Category	Data	Source
<b>Physical infrastructure</b>	Coal	Global Energy Monitor <sup>38</sup>
	Hydro, gas, oil, biomass	Global Data Power <sup>37</sup>
	Solar	China Energy Portal <sup>57</sup>
	Wind	China National Energy Administration <sup>58</sup>
<b>Fuel consumption rates</b>	High-voltage transmission lines (500 kV or more)	China National Energy Administration, Chen et al., Guo et al., Yi et al. <sup>26,59-61</sup>
	Coal	Global Energy Monitor <sup>38</sup>
<b>Emission factors</b>	Gas	Guo et al., Zhang et al. <sup>33,62</sup>
	Nuclear	Zhang et al. <sup>62</sup>
	Biomass	Hui et al., Wang et al. <sup>63,64</sup>
<b>Status of emissions control devices</b>	Coal CO <sub>2</sub>	Global Energy Monitor, IPCC <sup>38,65</sup>
	Coal NO <sub>x</sub> , SO <sub>2</sub> , PM <sub>2.5</sub>	Liu et al. <sup>66</sup>
	Gas, oil NO <sub>x</sub>	Gonzalez-Salazar et al. <sup>67</sup>
<b>Maximum production from renewable sources</b>	Coal NO <sub>x</sub> , SO <sub>2</sub>	Ministry of Ecology and Environment of the People's Republic of China <sup>68,69</sup>
	Coal PM <sub>2.5</sub>	Liu et al. <sup>66</sup>
<b>Fuel prices</b>	Hourly meteorological conditions	Gelaro et al. <sup>70</sup>
	Wind turbines power curves	Davidson et al., Hernandez et al., Natsheh et al. <sup>71-73</sup>
	Solar generators power curves	Li et al., Natsheh et al., Peng et al. <sup>23,73,74</sup>
	Seasonal hydro capacity factors by season	Guo et al. <sup>60</sup>
<b>Feed-in tariffs</b>	Coal, gas	Guo et al. <sup>33</sup>
	Biomass	Gosens et al. <sup>75</sup>
	Nuclear	Cheng et al. <sup>76</sup>
<b>Capital costs and operations and maintenance costs</b>	All sources	China National Energy Administration <sup>77</sup>
<b>Transmission costs</b>	All sources	OECD <sup>78</sup>
<b>Power demand</b>	All sources	Lin and Wu <sup>79</sup>
	Baseline	National Bureau of Statistics of China <sup>34</sup>
	Seasonal patterns	Guo et al. <sup>60</sup>
	Daily and weekly profiles, and charging characteristics	Chen et al. <sup>26</sup>
	Total EV demand	IIASA <sup>32</sup>

4

5

1 **S3. Results obtained with the 2022 power grid**

2 This section introduces the detailed results obtained with the 2022 power grid, including the  
3 source of electricity generation for EVs, changes in emissions, and premature mortality.

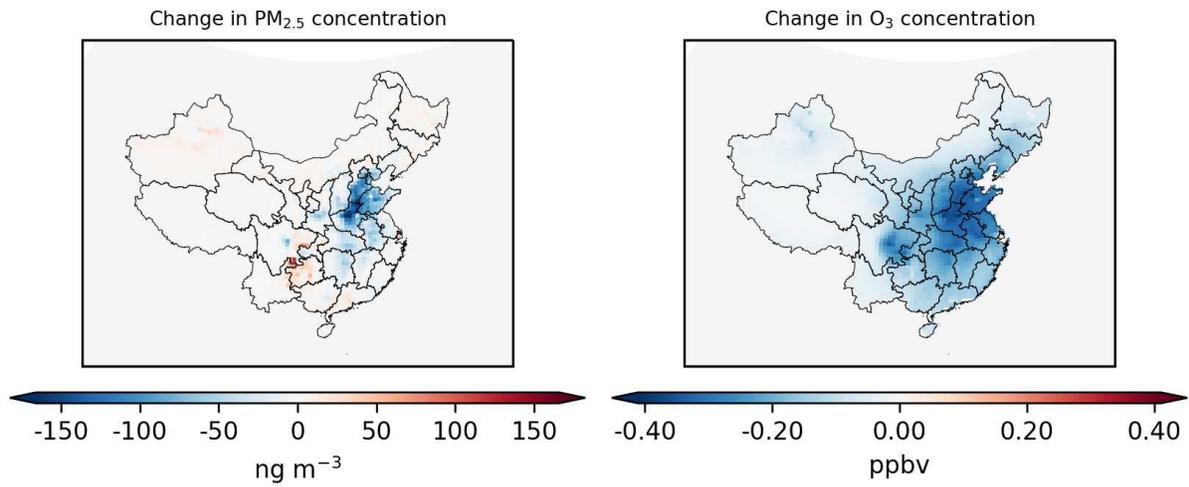
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5 **S3.1. Consequential emissions with the 2022 power grid**

6 To identify the effect of changes in the Chinese power grid, we repeat the power grid analysis  
7 with the projected 2022 power grid. As older power plants are phased out and new, less coal-  
8 reliant capacity with state-of-the-art emissions controls is installed (see Methods for details), we  
9 find that the consequential capacity that is dispatched in the EV scenarios is also less reliant on  
10 coal and has lower emission factors than its 2017 counterpart. Similarly to the 2017 power grid,  
11 we estimate that the consequential capacity available to meet the EV load under the slow, fast,  
12 and smart charging scenarios still has higher emission factors than the grid averages (54-86%,  
13 57-95%, and 55-71%, respectively). Figure S4 below summarizes these findings.

14





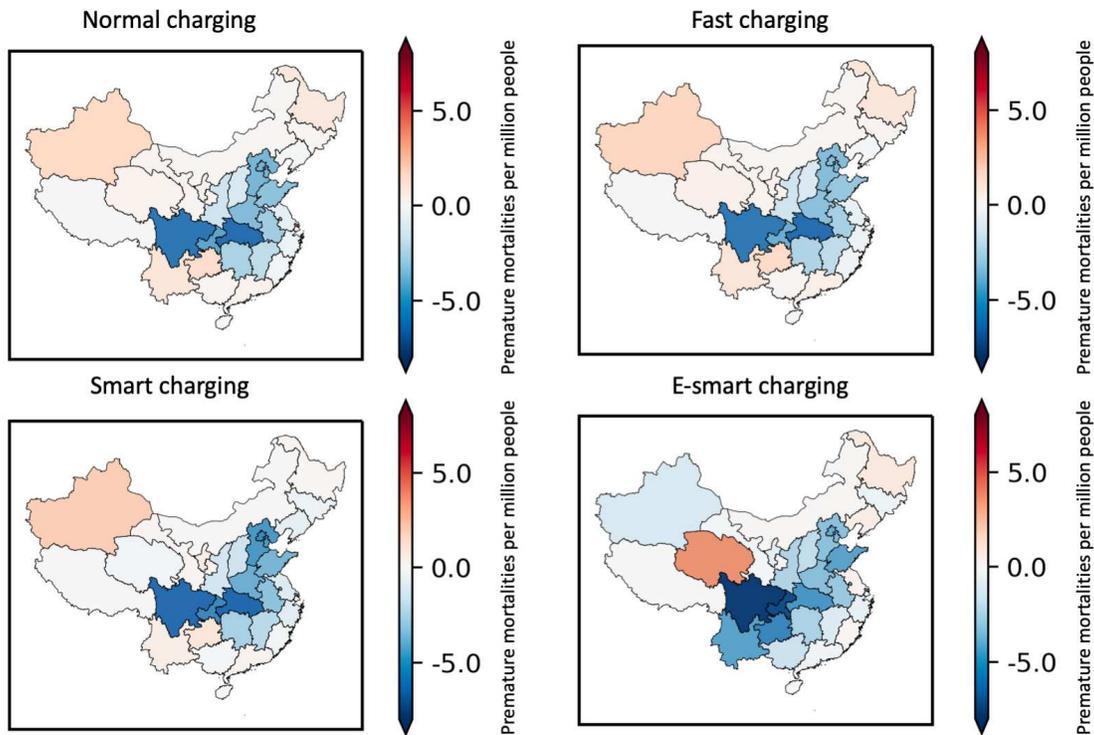
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**Figure S5. Changes in air quality under a slow charging scenario with displacement of conventional vehicles.**

Left: change in annual average PM<sub>2.5</sub> concentrations. Right: changes in mean 8-hour maximum daily average (MDA8) concentrations

### S3.3. Predicted health impacts obtained with the 2022 power grid

The changes in ground-level PM<sub>2.5</sub> and ozone concentrations obtained with the 2022 power grid and described above result in the province-level health impacts summarized in Figure S6 below.



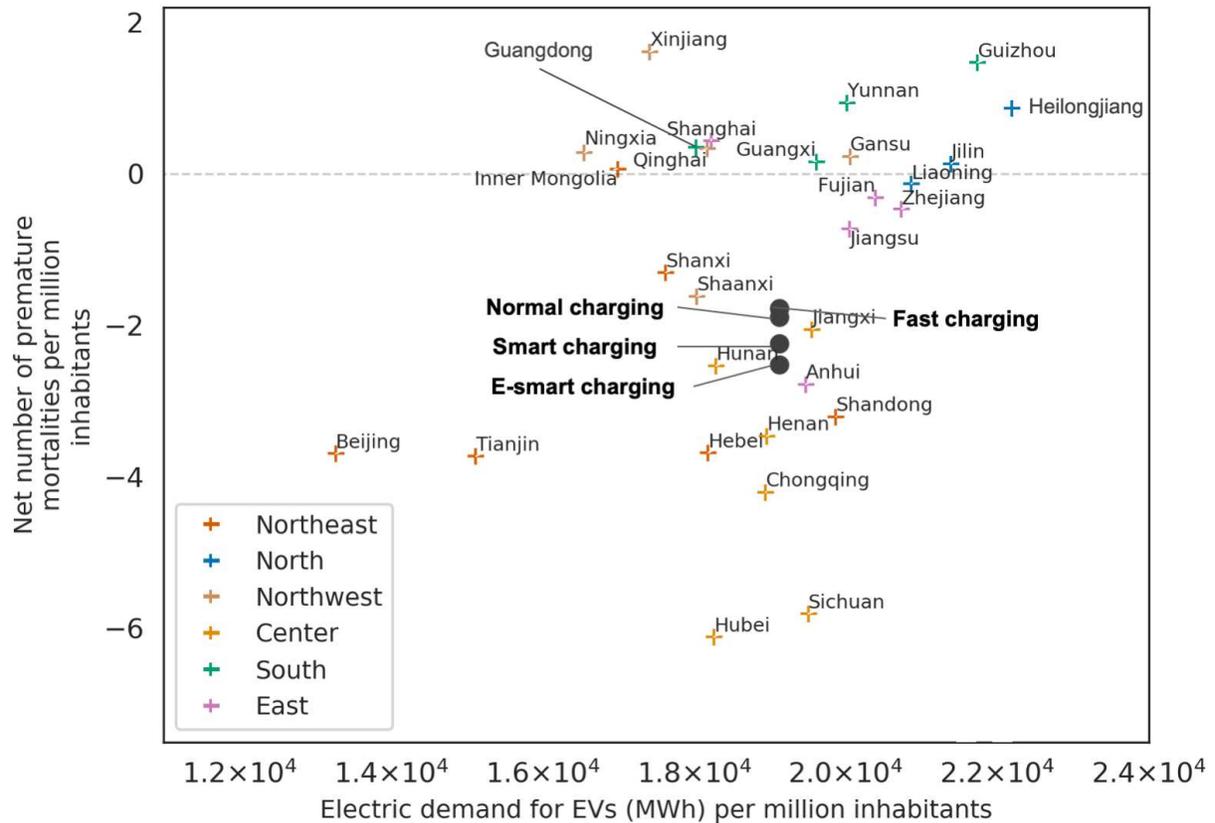
1

2 **Figure S6. Changes in the number of air pollution-related premature mortalities under different charging**  
 3 **scenarios.**

4

5 We estimate that premature mortalities under the slow and fast charging scenario reduce in  
 6 Eastern and Southern provinces, where we predict that the 2022 power grid will allow for net air  
 7 quality benefits in these provinces. On the contrary, Northeastern provinces will see an increase  
 8 in premature mortalities under these two scenarios. Smart charging with carbon pricing (e-  
 9 smart) with the 2022 power grid had smaller air quality benefits than with the 2017 power grid. In  
 10 particular, Northeastern provinces experience increased mortalities under the e-smart charging  
 11 scenario. However, the total number of premature mortalities decreases under all scenarios  
 12 compared to the 2017 power grid case, as summarized in Figure 7 of the main text and Figure  
 13 S7 below.

14



1  
 2 **Figure S7. Number of premature mortalities per capita vs electric demand for EVs per capita by province**  
 3 **estimated using the 2022 power grid.** Labeled crosses represent provinces while dots represent total values for  
 4 each scenario. Crosses are colored by regional power grid (North, Northeast, Northwest, East, Center, and South).

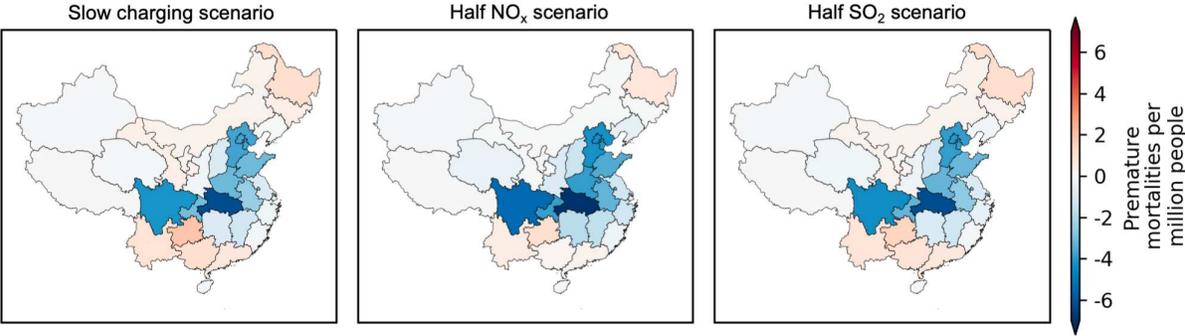
5  
 6 **S4. Results sensitivity**

7 This section presents the results of the following sensitivity analyses: power plant emissions  
 8 factors (S4.1), EV load allocation (S4.2), concentration-response function (S4.3), and nitrate  
 9 mechanism in GEOS-Chem (S4.4).

10  
 11 **S4.1. Result sensitivity to power plant emissions factors**

12 Tang et al.<sup>43</sup> suggest that emissions reported in Zheng et al.<sup>80</sup>, which correspond to the ones  
 13 reported in MEIC<sup>65,81</sup> and used to calibrate our model, might overestimate SO<sub>2</sub> by as much as  
 14 56%. They also find that NO<sub>x</sub> and PM<sub>2.5</sub> emissions from real-time monitoring are 68% and 89%

1 lower than reported in Zheng et al<sup>80</sup>, respectively. To investigate the potential effect of this  
 2 discrepancy on our results, we conducted additional simulations reducing either power plants  
 3 NO<sub>x</sub> or SO<sub>2</sub> emissions factors by half. We find that power plant NO<sub>x</sub> emissions have the largest  
 4 impact on air pollution-related health impacts, as the total number of additional premature  
 5 mortalities under the slow charging scenario decreases by 23% when power plant NO<sub>x</sub>  
 6 emissions factors are reduced by 50%. NO<sub>x</sub> emissions reductions lead to decreases in PM<sub>2.5</sub>  
 7 concentrations everywhere, but cause increases in ozone concentrations in NO<sub>x</sub>-saturated  
 8 areas<sup>82</sup>. In the sensitivity case where power plant SO<sub>2</sub> emissions factors are reduced by half, we  
 9 find a decrease of 4% in the total number of additional air pollution-related premature mortalities  
 10 under the slow charging scenario. The province-level impacts under the slow charging scenario  
 11 in each of these cases is presented in Figure S8 below.



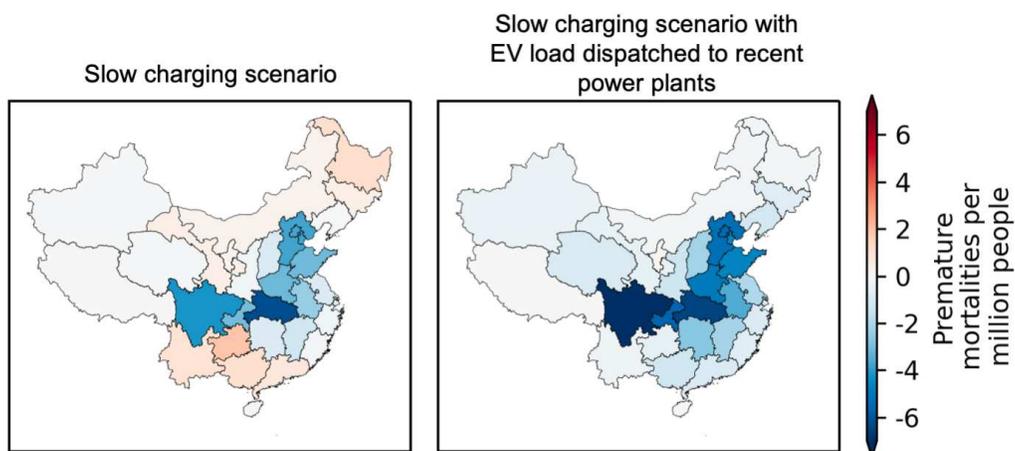
12  
 13 **Figure S8. Total number of premature mortalities by region under the slow charging scenario in the 50% NO<sub>x</sub>**  
 14 **and 50% SO<sub>2</sub> sensitivity cases.**

16 Compared to the results reported in the main text, the half-NO<sub>x</sub> sensitivity case causes net  
 17 health impacts to be negative in most of Eastern and Southern China, while Northeastern China  
 18 still experiences an increased number of premature mortalities.

22 **S4.2. Result sensitivity to the EV load allocation**

1 Despite the fact that no major grid changes occur during the EV deployment considered in this  
2 study<sup>38</sup>, some new generators are deployed along with EVs between 2017 and 2020. To  
3 account for the fact that under such circumstances, the consequential approach used in the  
4 main text does not fully capture the emissions change, we consider a sensitivity scenario where  
5 the EV load is matched exclusively by power plants built after 2017 and equipped with the most  
6 stringent emission control devices (see Methods for details). In this case, we find that the  
7 modeled EV deployment under the slow charging case with the current becomes net beneficial,  
8 reducing premature mortalities by 160 nationwide and CO<sub>2</sub> emissions by 5.6 Tg. In this  
9 scenario, the spatial distribution of impacts is also modified (see Figure S9).

10



11  
12 **Figure S9. Air quality impacts associated with the modeled EV development in the slow charging conditions**  
13 **in the slow charging scenario** described in the main text (left) and assuming that the EV load is matched  
14 exclusively by recent generators (right).

15  
16 In this sensitivity case, 14 out of 29 provinces have reductions in air pollution-related mortalities.  
17 The major difference is the Northeastern provinces. In the main case, EV deployment is  
18 associated with an increase in mortality, while in the sensitivity case they have net air quality  
19 benefits associated with EV deployment. This further highlights the point made in the main text

1 that the deployment of a cleaner grid in the Northeast has the potential to avoid the negative  
2 impacts calculated.

3

#### 4 **S4.3. Result sensitivity to the choice of the concentration-response function**

5 When using the concentration-response function (CRF) from the Global Burden of Disease  
6 2015 (GBD 2015) study<sup>37</sup>, we find that the number of avoided premature mortalities attributable  
7 to changes in PM<sub>2.5</sub> concentrations in the slow charging scenario decreases by 65% to ~300  
8 (95% CI: 100–500) avoided premature mortalities. With a central estimate for ozone impacts of  
9 ~1,100 (95% CI: 800–1,400) fewer premature mortalities, this means that the net impact of the  
10 slow charging scenario is ~1,400 (95% CI: 800–2,000) avoided premature mortalities per year.  
11 The spatial distribution of impacts is not modified. In contrast, when using the CRF from Hoek et  
12 al.<sup>75</sup>, the number of PM<sub>2.5</sub>-related mortalities increases by 13% to ~900 (95% CI: 700–1,100)  
13 avoided premature mortalities, bringing the net number of avoided mortalities to ~2,000 (95%  
14 CI: 1,500–2,500).

15

16 In the case of ozone, using the CRF based on the daily 1-hour maximum during the ozone  
17 season from Jerrett et al.<sup>83</sup> yields 33% greater reduction in ozone-related premature mortalities,  
18 bringing the total number of avoided mortalities in the slow charging scenario to ~2,300 (95%  
19 CI: 1,700–2,900). The spatial distribution of the impacts is not modified.

20

#### 21 **S4.4. Result sensitivity to the GEOS-Chem nitrate mechanism**

22 Previous studies pointed out that the GEOS-Chem model might overestimate nitrate  
23 production<sup>45</sup>. One proposed solution is to decrease the HNO<sub>3</sub> concentration in the input to the  
24 thermodynamic gas and particle partitioning by 25% at each time step<sup>44</sup>. We implement this fix  
25 and find that the total number of premature mortalities in the slow charging scenario decreases  
26 by 36% to -2,200. It reduces the impact of EVs in all scenarios on PM<sub>2.5</sub> concentrations by 32%,

1 but also reduces the total benefits of reducing on-road and refineries emissions. These results  
 2 should however be interpreted with caution as the corrected mechanism has been questioned<sup>45</sup>  
 3 and the corrected simulations yield a lower  $r^2$ -correlation with monitor data (see Section S5.2).

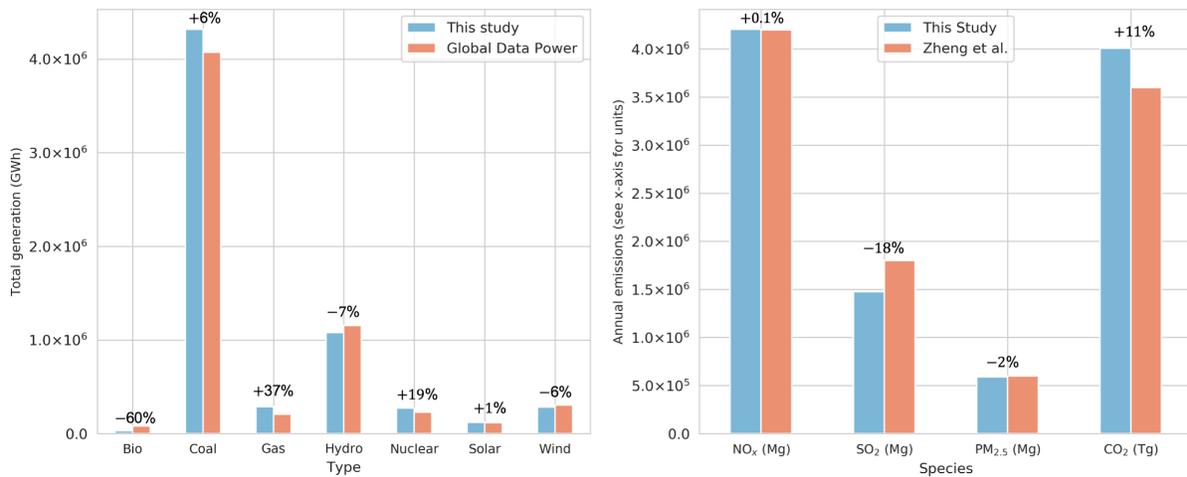
4  
 5 **S5. Validation of the power grid and air quality models**

6 This section details the methods and the results obtained when comparing the results in our  
 7 power grid (S5.1) and air quality (S5.2) models to data from the literature.

8  
 9 **S5.1. Validation of the power grid model**

10 To validate our power grid model, we compare our generation estimates with source-specific  
 11 generation data from the Global Data Power database<sup>38</sup> and our emissions results with those  
 12 presented in Zheng et al.<sup>80</sup>. Total generation and total emissions for the year 2017 from Zheng  
 13 et al.<sup>80</sup> and from this study are represented side-to-side on figure S10 below.

14



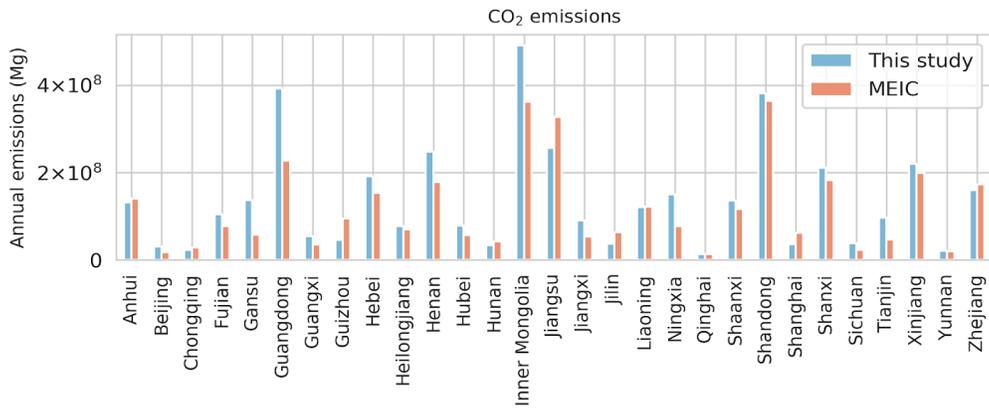
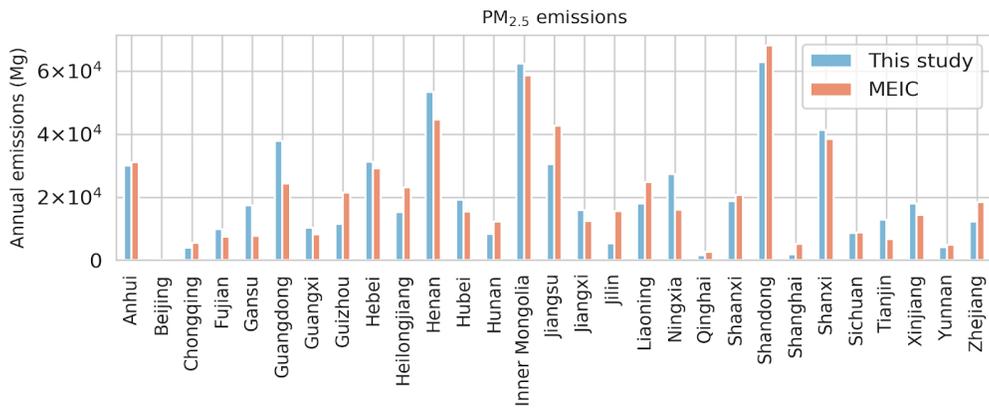
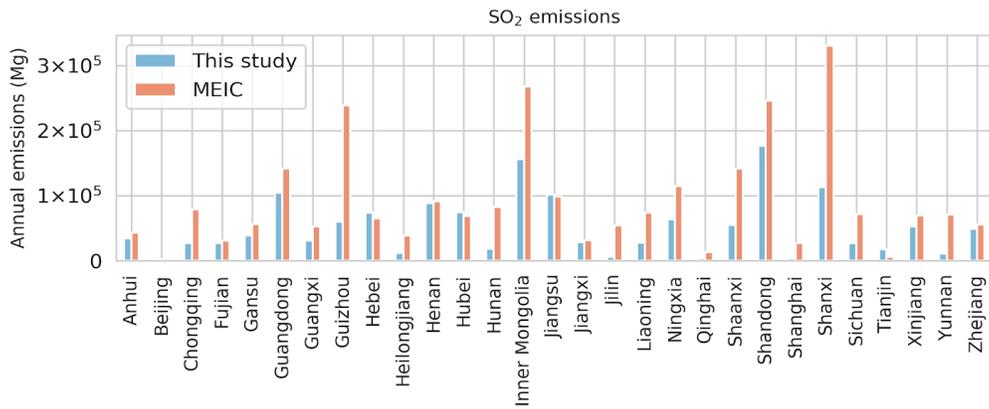
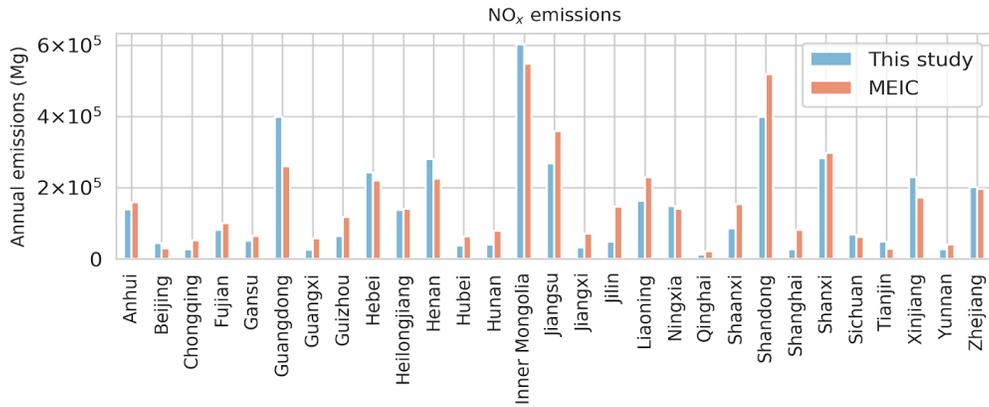
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16 **Figure S10. Comparison between total annual generation in this study and Global Data Power<sup>38</sup> and between**  
 17 **total annual emissions in this study and in Zheng et al.<sup>80</sup>. Percent relative changes between this study and the**

18 reference figures are shown on top of bars.

19

1 We also compared province-level emissions levels between this study and the Multi-resolution  
2 Emission Inventory for China (MEIC) inventory v1.3<sup>65,81</sup> for 2016, available at  
3 <http://meicmodel.org/>. The results are represented side-to-side on figure S9 below. MEIC  
4 emissions are for 2016, as 2017 estimates were not available at the time of writing.

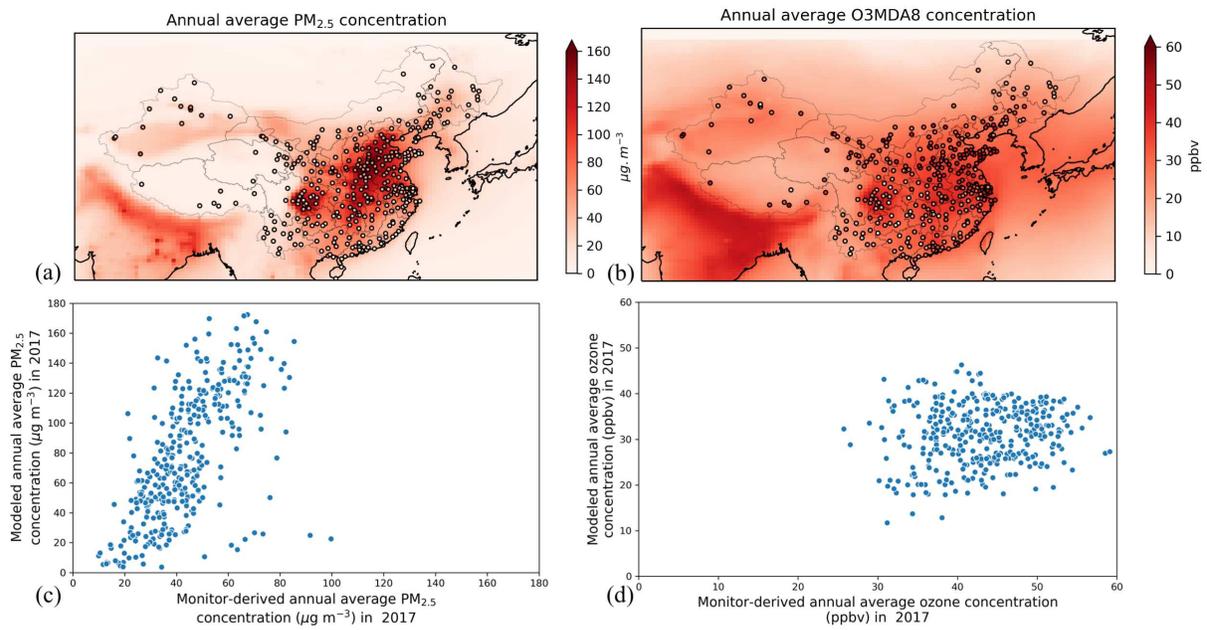


1 **Figure S11. Comparison by pollutant between annual emissions by province in this study and MEIC<sup>65,81</sup>.**

2  
3 The largest differences in emissions between this study and the MEIC inventory lie in SO<sub>2</sub>  
4 emissions. This is likely due to different underlying assumptions about the sulfur content of coal  
5 in each region as well as operational status of flue-gas desulfurization<sup>81</sup>. Furthermore, Tang et  
6 al.<sup>43</sup> suggest that emissions reported in Zheng et al.<sup>80</sup>, which correspond to the ones reported in  
7 MEIC, might overestimate SO<sub>2</sub> by as much as 56%. They also find that NO<sub>x</sub> and PM<sub>2.5</sub>  
8 emissions from real-time monitoring are 68% and 89% lower than reported in Zheng et al<sup>80</sup>,  
9 respectively. To investigate the effect of this discrepancy on our results, we conducted  
10 additional simulations reducing power plants emissions factors accordingly. The results are  
11 presented in Fig S11.

## 12 13 **S5.2. Validation of the air quality model**

14 To validate our chemical-transport model, we compare predicted PM<sub>2.5</sub> and ozone  
15 concentrations with a widely used<sup>44,84</sup> dataset of observations collected hourly from air quality  
16 monitors in 360 cities in China for the year 2017. Results for PM<sub>2.5</sub> and ozone MDA8 are  
17 presented below. We find a squared correlation coefficient ( $R^2$ ) of 0.41 for PM<sub>2.5</sub> and 0.02 for  
18 ozone MDA8, comparable to other evaluations of GEOS-Chem<sup>85</sup>.



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**Figure S12. Comparison between predicted (a) and (c) PM<sub>2.5</sub> and (b) and (d) ozone MDA8 concentrations for 2017 and monitor data from 360 locations.**

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