Supplementary Information

An integrated assessment of emissions, air quality, and public health impacts of China's transitions to electric vehicles

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1. Integrative framework for environmental impact assessment

One of the major novelties in this work is the linkage between policy scenario construction, private vehicle fleet modeling, air quality modeling, and climate change and health impact assessment. Fleet size estimation is integrated into policy scenario analysis for subsequent climate and health impact quantification. This linkage allows us to capture the environmental impacts of diminished/avoided motorization due to electric vehicle policies, which has been ignored in the existing studies for air quality impact assessment of vehicle electrification. The integrative framework for understanding how sustainable mobility policy alters the vehicle ownership demand and the corresponding environmental externalities is presented in Figure S1. Another major novelty is in the fleet model development which would be described in more detailed below (*).

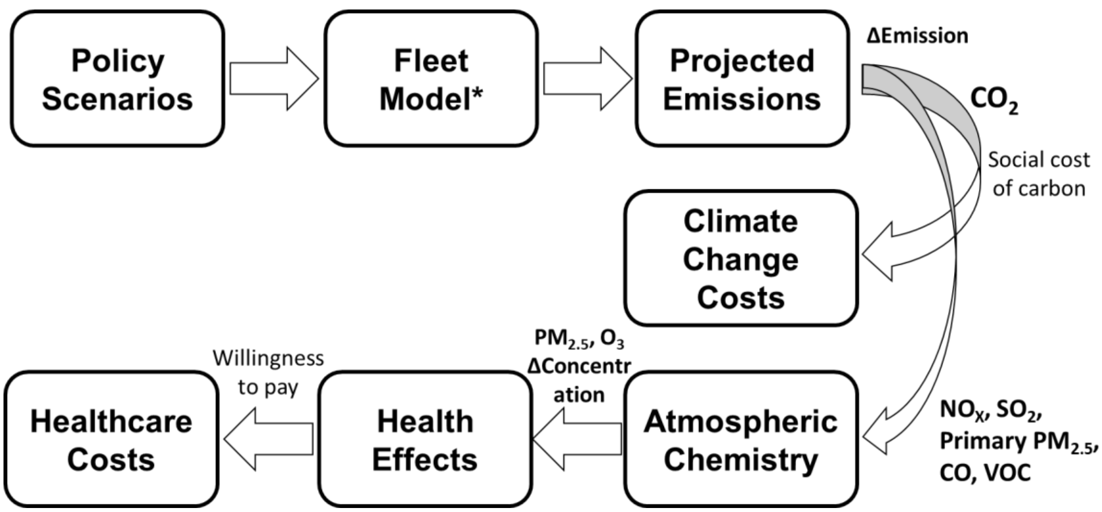


Figure S1. Integrated assessment framework of emissions, air quality, climate and health impact assessment

*We make contributions to modeling practices in the following three aspects:

1) Vehicle market size estimation (Supplementary information 4):

- The developed fleet model is able to perform nationwide as well as detailed subnational level analysis on oil demand, CO2 emissions, and air pollutants of the private vehicle sector, considering provincial differences in economic development, vehicle market maturity, and vehicle use intensity.
- Interprovincial migration model is built and incorporated into the fleet model to capture people flows across provinces.

- Impact of city-level car ownership restriction policy on the provincial car fleet is investigated and incorporated into the fleet size estimation.

2) Well-to-tank stage emissions (Supplementary information 6):

- Interprovincial electricity transmission is taken into account when calculating provincial grid carbon intensity.
- The most up-to-date air pollutant emission factors (i.e., 2017) of regional electricity generation are used in the air pollutant calculation.

3) Tank-to-wheel stage emissions (Supplementary information 6):

- Provincial heterogeneity in real-world fuel consumption (varying by weather, traffic, driver behavior, and fuel quality) is considered when computing oil demand and carbon footprint.
- Provincial-level on-road air pollutant emission factors of gasoline-powered cars (varying by vehicle technology, climate, temperature, altitude, fuel quality and so on) are derived and applied in this work.

2. Technical parameters of the reference vehicles

CO_2 emissions from vehicle manufacturing are derived from multiple sources [1–5] and adjusted based on the reference cars weights and battery capacity. Since there was a very limited number of conventional hybrid electric vehicles (HEVs) being sold in China, the fuel consumption rate and manufacturing emissions of HEV are assumed to be 33% less and 27% more than that of the counterpart ICEV [6]. Parameters for ICEV, HEV, PHEV, and BEV are summarized in Table S1 (more details about vehicle specifications car be found in [7]).

Table S1. Summary of the reference vehicle technical parameters

Vehicle Technology	ICEV	HEV	PHEV	BEV
Fuel consumption	7.6 L/100 km	5.1 L/100 km	6.0 L/100km 18.6 kWh/100km	14.4 kWh/100 km
Curb weight and battery capacity	1,280 kg	--	1,623 kg; 11.9 kWh NMC	1,619 kg; 50.5 kWh NMC
Emissions from vehicle manufacture (tons CO_2)	8.1	10.3	11.3 (including battery 1.4 tons CO_2)	15.5 (including battery 4.1 tons CO_2)

3. EV penetration pattern in *EV SCENARIO*

In *EV SCENARIO*, we expect that the markets having higher EV cumulative sales today, stronger EV policies (including EV purchase subsidies and green license plate for EVs), a greater variety of EV models, and more charging infrastructure will all reinforce those provinces' leadership position in the EV sales performance by 2030. In other words, we assume that the provinces that are currently leading the national EVs sales will continue to dominate through 2030 in the EV scenario. So far, a limited number of provinces account for a majority of EV sales in China—Tianjin, Beijing, Zhejiang, Hubei, Shanghai, Sichuan, and Henan collectively contribute to about 50% of the current EV cumulative sales[8].

"Open market index of new energy vehicle" was used to describe the differences in EV brand/model variety and EV market penetration rate across provinces in China [9]. Provinces with a higher open market index are considered more acceptable to this new vehicle technology and with fewer EV adoption barriers (such as charging convenience, EV purchase price, and familiarity). We categorize 31 provinces into four groups based on their open market index documented in the iCET report [9], as shown in Table S2.

Table S2. Group categorization for new energy vehicle (NEV) open market index and their contribution to the national cumulative EV sales in the end of 2017

NEV open market index	Province	Cumulative EV sales share in 2017 (%)
Group 1 (k=1)	Tianjin, Beijing, Zhejiang, Hubei, Shanghai, Sichuan, Henan	50
Group 2 (k=2)	Fujian, Jiangsu, Shaanxi, Guangdong, Shandong, Hebei, Hunan, Shanxi	37
Group 3 (k=3)	Chongqing, Yunnan, Anhui, Guangxi, Jiangxi	10
Group 4 (k=4)	Inner Mongolia, Liaoning, Jilin, Heilongjiang, Guizhou, Gansu, Qinghai, Ningxia, Xinjiang	3

Projecting future EV sales at province level is uncertain. In *EV SCENARIO*, we assume that the provincial EV sales growth would follow Equation (S1), meaning that the incremental increase in EV sales in group k would be proportional to its contribution to the nationwide EV cumulative sales by 2017 (see Table S2 for the contribution percentage); the incremental increase in EV sales in province *p* in group *k* would be proportional to its contribution to the group vehicle sales in year *i*.

$$\mathbf{Sales_{p,i,EV}} = \mathbf{Sales_{p,i\text{-}1,EV}} + \Delta\mathbf{Sales_{N,i,EV}} \times \frac{\sum_{\boldsymbol{p}\in\boldsymbol{k}} \mathbf{CumSales_{p,2017,EV}}}{\mathbf{CumSales_{N,2017,EV}}} \times \frac{\mathbf{Sales_{p,i}}}{\sum_{\boldsymbol{p}\in\boldsymbol{k}} \mathbf{Sales_{p,i}}} \quad \text{(S1)}$$

where $\mathrm{Sales_{p,i,EV}}$ is EV sales in province *p* in year *i*; $\Delta\mathrm{Sales_{N,i,EV}}$ ($=\mathrm{Sales_{N,i,EV}}-\mathrm{Sales_{N,i\text{-}1,EV}}$) is the national increase in EV sales in year *i*; $\sum_{(\boldsymbol{p}\in\boldsymbol{k})}\mathrm{CumSales_{p,2017,EV}}$ is the provincial sum of the cumulative EV sales in NEV market open index group k in 2017; $\mathrm{CumSales_{N,2017,EV}}$ is the national cumulative EV sales in 2017; $\mathrm{Sales_{p,i}}$ is private car sales in province *p* in year *i*; $\sum_{(\boldsymbol{p}\in\boldsymbol{k})}\mathrm{Sales_{p,i}}$ is the provincial sum of the private car sales in NEV market open index group k in year *i*.

It is noted that the national EV sales are expected to keep growing owing to the dual-credit mandate. EV sales projection at national level is detailed in our previous study [10]: we estimate that EVs will account for 21% and 37% of the total private passenger vehicle market share in 2025 and 2030.

4. Private vehicle fleet size projection

The car stock and sales model at the national level is briefly described here. The model calculates the total private car stock in year *i* ($\hat{V}_i$) by integrating the product of the income distribution density (I) and the propensity that an individual with that purchasing power owns a car (g):

$$\hat{V}_i = P_i \int_{A=0}^{\infty} I_i(A) g(A) dA \quad \text{(S2)}$$

Where A = car affordability index, which is per-capita disposable income level (x) divided by car price index (p). P_i = population in year *i*. I_i = income distribution function for year *i*, simulated using the log-logistic function with a given Gini index and mean per-capita disposable income. The projected compound annual growth rate of mean per-capita disposable income at the provincial level is assumed to be the same as the per-capita GDP growth rate from the China Regional Energy Model (C-REM)[11]; due to limited data availability, provincial Gini index is assumed to be constant from 2016 to 2030. $g(A)$ = Gompertz function describing the probability of owning a car as a function of affordability index. Fitting the Gompertz function (i.e., $g(A) = \gamma \exp(-\alpha\, exp(-\beta A)))$ requires the estimation of three shape parameters— α, β, and γ—from historic data on household car ownership as a function of car affordability.

Below we explain how we disaggregate the national-level fleet model by provinces and how we evaluate the impacts of city-level car ownership restriction policy on provincial car fleet.

4.1 Disaggregating the national model by province (no car ownership restriction policy counterfactual):

4.1.1 The car ownership function, g(x, pi)

Much of the uncertainty in China's future private car stock stems from data limitations for estimating the γ parameter for the Gompertz function, which represents the eventual probability of possessing a car when people have high purchasing power. Gompertz function curves (g) are expected to be varied across provinces depending on the urban population density, auto dependency, mobility levels across all modes, road infrastructure investment, consumer preference, and so on. Figure S2(a) shows the historical relationship (2013-2016) between car ownership level (i.e., cars per 100 people) versus per-capita disposable income at a provincial level. Shanghai was an early adopter of license auctioning, putting the policy in place in 1994 before motorization had really picked up. Beijing, on the other hand, did not implement its own car restriction system until 2011 when its private car had hit to 4 million.

Thus, when we compute the saturation parameters of the Gompertz function (γ) at a provincial level, we exclude Shanghai because the license plate quota policy has obscured the underlying relationship between the probability of owning a car and car affordability. Figure S2(b) depicts the resulting mean Gompertz curves that are obtained from 300 samples of γ with the associated probability distribution from Monte Carlo simulation. For Shanghai, we assume its γ is the same as that of the city cluster 1 (discussed in Supplementary information 4.1.2).

(a) **(b)**

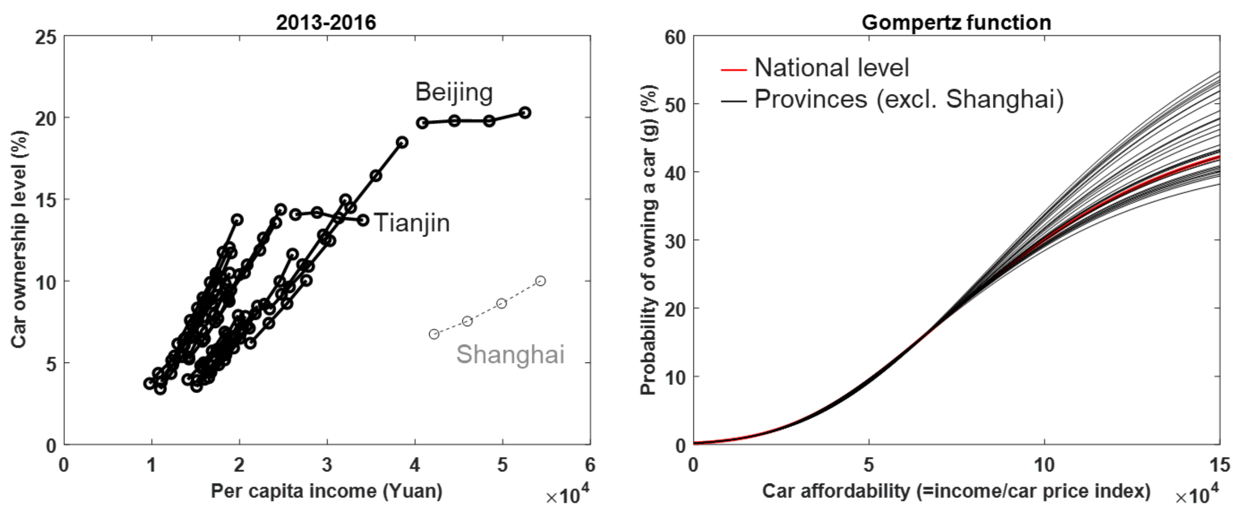


Figure S2. (a) Private car ownership level versus per capita disposable income at the provincial level; (b) the computed Gompertz function curves that describe the probability of owning a car versus car affordability at both national and provincial level in China; Shanghai is excluded because its early adoption of license plate quota policy had obscured the underlying relationship.

4.1.2 Shanghai: Mapping Provinces to City Cluster 1

Four city types were previously established in the literature, derived from trends in urbanization and motorization patterns for 287 Chinese municipal administrative areas for the period from 2001-2014 [12]:

1. Large, wealthy cities with metro rail systems (N = 23, including *Shanghai*, Beijing, Guangzhou, Shenzhen, Tianjin, and Hangzhou),

2. Low-density, wealthy cities with auto-oriented mobility patterns (N = 41, including Haikou and Sanya in Hainan Province),
3. Low-density, medium-wealth cities with moderate mobility (N = 134), and
4. High-density, low-wealth cities with lower mobility levels (N = 89).

The most disaggregate form of easily available data for our fleet model is at the provincial level. So we begin by estimating the saturation parameters (γ_p) of car ownership function (i.e., $g(x, p_i)$) for each of the 30 provinces in China, excluding Shanghai (Figure S2(b)). Next we map the province-level models to the four city clusters using a method presumably similar to that used by Gan et al. (2019) [13]. While Gan et al. (2019) used car stock as the weighting factor, we use GDP. GDP is often used for projecting vehicle ownership [14,15] and is therefore the best proxy available for car purchasing characteristics in the absence of information on income and car price before 1994 in Shanghai. It is noted that here we only focus on city cluster 1 to which Shanghai province belongs.

We calculate γ_{c1} for cluster 1 by taking the average of the provincial parameters weighted by the proportion of cluster GDP contributed by each province (w_p):

$$\gamma_{c1} = \sum_{p=1}^{30} w_p \gamma_p = \sum_{p=1}^{30} \frac{GDP_{p,c1}}{GDP_{c1}} (\gamma_p) = \gamma_{SH} \quad \text{(S3)}$$

where $w_p = \frac{GDP_{p,c}}{GDP_c}$, GDP_c is the total GDP of all cities in cluster *c1* and $GDP_{p,c1}$ is the total GDP of the cities in province p that are assigned to cluster *c1*, such that $\sum_{p=1}^{30} w_p = 1$. α_{c1} and β_{c1} are then determined by regression to historical data at a given γ_{c1}. We assume the saturation parameter of Shanghai (γ_{SH}) and the other two shape parameters (α_{SH} and β_{SH}) are the same as that of city cluster 1.

4.1.3 Population: Interprovincial migration model, P_i

Migrants are defined as individuals who changed their province of permanent residence during each five-year period. Gravity model has been widely applied and expanded to include factors like economic well-being to simulate migration flows. Similar to X. Luo et al. (2016) [16], we model interprovincial migration flows based on population numbers and per capita GDP levels of both the origin and destination provinces, as well as the past migration patterns. Including past migration as an independent variable is to reflect structural factors (such as distance and transport linkages) that might affect migration decisions. Data include migration flows between each pair of 31 provinces for the four-time period (1995–2000, 2005–2010, and 2010-2015 from the national census; 2000-2005 derived from the X. Luo et al. (2016)). The log-log migration model is created using Poisson distribution[1] and linear regression; the resulting model is presented below:

$$\ln(M_{io,t}) = -0.33115 + 0.02873 \ln(pop_{i,t-1}) + 0.11987 \ln(pop_{o,t-1}) + 0.11526 \ln(GDPcap_{i,t-1}) - 0.17861 \ln(GDPcap_{o,t-1}) + 0.86724 \ln(M_{io,t-1}) \quad (S4)$$

where the dependent variable $M_{io,t}$ represents the number of migrants moving from province o to province i, time t; the independent variables include population of the destination and the origin province, time t-1, GDP per capita of the destination and the origin province, time t-1, and the number of migrants moving from province o to province i, time t-1.

The model reveals that 1) the projected migration would primarily reflect the past migration; 2) the effect of GDP is more significant than that of population. Figure S3 shows the historical and projected number of migrants, suggesting that the migration volume will be stabilizing around 60 million people per each time period; this is due to a decline in economic well-being differences between in- and out-migration provinces. Figure S4 presents the net migration flows at provincial level projected in the period of 2025-2030.

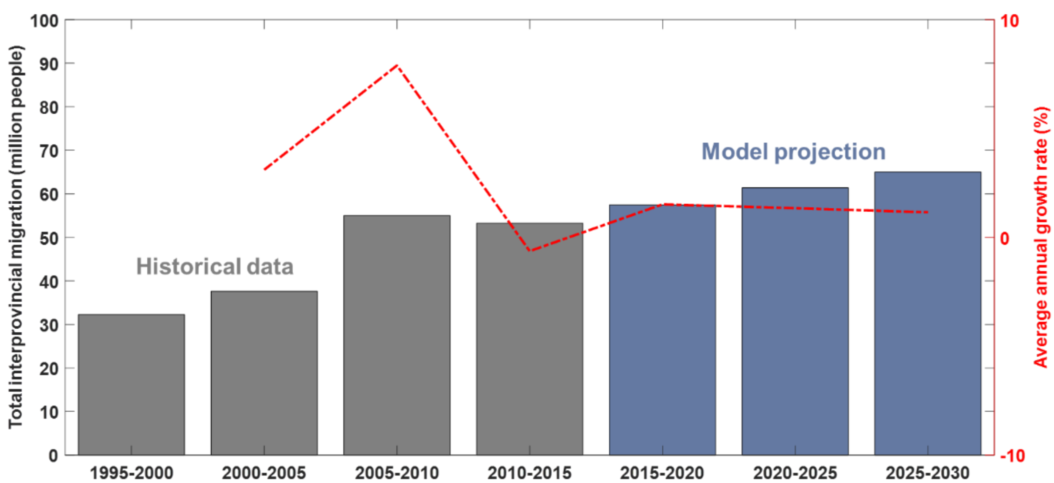


Figure S3. Total historical and projected migration volume (shown in bar chart; left ordinate) and annual migration growth rate (shown in dashed red line; right ordinate)

[1] A discrete probability distribution for the counts of events that occur randomly in a given interval of time or space.

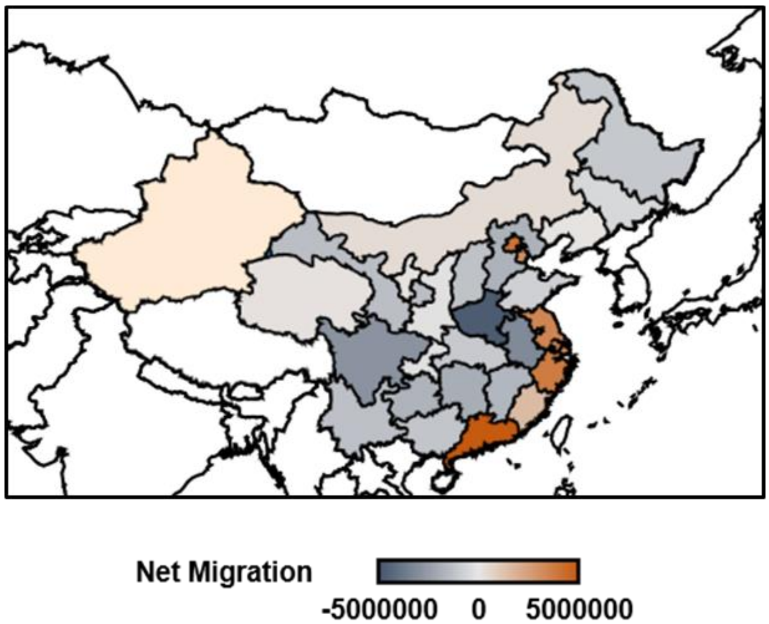


Figure S4. Net interprovincial migration flow map during 2025-2030: The colors describe the net interprovincial migration across the major Chinese provinces. Blue indicates net emigration provinces, and orange indicates the net immigration provinces.

Note: GeoNames[17] *is used for data visualization and only the provinces of China modeled in the present work are shown using colors in the figure.*

4.2 Incorporating municipal car ownership restriction policies

4.2.1 Background

Continuing motorization, accompanied by trends of urbanization and sprawl, is putting pressure on China's cities in the form of rising congestion and local air pollution [18,19]. To combat these issues some of China's megacities are adopting car ownership restrictions, which limit growth in new-purchase vehicle sales by rationing the number of new license plates in a city and allocating these licenses through lottery or auction [20]. To date, six cities and one province have adopted stringent car ownership restriction policies (Table S3). Shanghai was the first to adopt such a policy in 1994 using an auction mechanism to allocate new vehicle licenses to those with the highest bid. In 2011, Beijing became the second city to adopt a car ownership restriction, opting for a pure lottery process. In 2012, Guangzhou adopted a hybrid policy that allows residents seeking vehicle licenses to opt-in to either an auction or a lottery. Other cities followed suit, with Tianjin and

Hangzhou adopting hybrid policies in 2014 and Shenzhen in 2015. In late 2018, the island province of Hainan also adopted an ownership restriction.

Table S3. Car Ownership Restriction Policies (as of Sept 2019)

City/Province	Adoption year	Policy type
Shanghai	1994	Auction
Beijing	2010	Lottery
Guangzhou	2012	Hybrid
Shenzhen	2014	Hybrid
Tianjin	2014	Hybrid
Hangzhou	2014	Hybrid
Hainan	2018	Hybrid

Notes: The cities of Guiyang and Shijiazhuang adopted less stringent restrictions on car sales in 2011 and 2013, respectively. Guiyang's policy uses a lottery to allocate a special kind of license plate to enter specific districts with serious congestion (generally, in the inner city). Shijiazhuang's policy does not allow households to purchase a third car.

Fearing the impact of additional city-level ownership restrictions on China's domestic car manufacturing industry—particularly with vehicle sales falling in 2018 for the first time since the 1990s—China's national government announced a new policy to temporarily stop local governments from implementing new restrictions on car purchases for 2019-2020 [21]. The policy also encouraged cities with existing car ownership restrictions to consider removing the vehicle quotas all together. Guangzhou and Shenzhen have responded by increasing the number of ICEV licenses that they will allocate in 2019 [22], while other cities with existing policies have yet to take any action to respond to this mandate.

4.2.2 Assumptions on status quo car ownership restriction policy

There remains significant uncertainty surrounding the long-term continuity and stringency of car restriction policy. In this study with the base model year of 2017, we consider the effects of status quo policy adoption – representing a future in which no additional cities adopt car ownership restriction policies, but the 6 municipal policies that do exist continue to be enforced through 2030.

We assume cities that adopt a car ownership restriction policy would cap first-time purchase vehicle sales at certain levels of economically driven counterfactual demand. The cap values are various across cities, derived from the average ratio of the actual number of vehicles sold via quota to counterfactual first-time purchase vehicle sales for 2016 and 2017 in the 6 cities that currently have car ownership restrictions (Table S4).

Table S4. Cap values derived from the comparison of demand to vehicles allocated (both in million vehicles) in 6 Chinese cities in 2016 and 2017

City	Demand: projected first-time purchase sales without quota policy		Quota: total vehicles actually allocated		Q/D		
	2016	2017	2016	2017	2016	2017	Avg
Shanghai	0.507	0.488	0.132	0.133	0.26	0.27	**0.27**
Beijing	0.533	0.567	0.082	0.083	0.15	0.15	**0.15**
Guangzhou*	0.571	0.588	0.089	0.107	0.16	0.18	**0.17**
Hangzhou*	0.547	0.563	0.070	0.065	0.13	0.12	**0.12**
Tianjin	0.340	0.352	0.073	0.072	0.21	0.20	**0.21**
Shenzhen*	0.263	0.250	0.056	0.057	0.21	0.23	**0.22**

* We first project the no-car-ownership-restriction demand for first-time purchase sales for Guangdong and Zhenjiang provinces, then we disaggregate the demand of these two provinces by city based on the GDP contribution of each city to the province GDP. Guangzhou city contributed about 25% of Guangdong province GDP; Hangzhou city contributed about 23% of Zhenjiang province GDP; Shenzhen city contributed about 24% of Guangdong province GDP.

In our defined status quo policy adoption, the six megacities in China that had car ownership restriction policies in 2017 (i.e., the base year in this study) continue to enforce these policies out to 2030, but no additional cities adopt the policy. Shanghai, Beijing, and Tianjin are province-level cities, so we apply the derived cap values (0.27, 0.15, and 0.21, respectively) to 100% of the projected economically-driven demand for first-time purchase sales in these three provinces. On the other hand, for the city-level quota policy's impacts on Guangdong and Zhenjiang provinces, we apply the cap values to only about 49% and 23% of each no-quota-policy first-time purchase projections; details are described as below:

- Guangdong: Guangzhou city and Shenzhen city represent 25% and 24% of Guangdong GDP, respectively, so we apply the cap values of 0.17 and 0.22 to 25% and 24% of the projected economically driven first-time purchases for Guangdong. And we allow the other 51% (=100%-25%-24%) of demand (representing the demand from the cities that currently do not have car ownership restriction policies in Guangdong) to remain uncapped through 2030.
- Zhenjiang: Hangzhou city represents 23% of Zhenjiang GDP, so we apply the cap value of 0.12 to 23% of the projected economically driven first-time purchases for Zhenjiang. We allow the other 77% (=100%-23%) of demand to remain uncapped through 2030.

The effect of car ownership restriction policy (starting from late 2018) on Hainan's fleet is expected to be mild; this is because the number of quotas allocated in 2019 in Hainan is found to be approximately equal to the province's economically driven first-time car purchase demand. As a result, we ignore the quota policy in the modeled Hainan's fleet projection and the potential bias to 2030 is likely to be small.

5. Vehicle kilometers traveled (VKT)

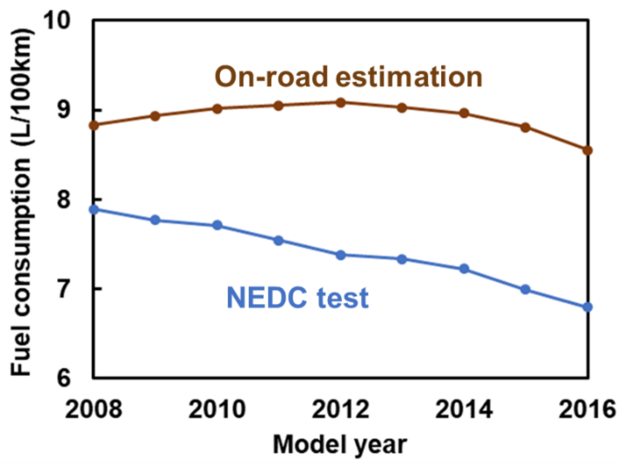
Based on the historical nationwide gasoline consumption (assuming 88% of which is consumed by private gasoline-powered car [23]), on-road fuel consumption (Figure S5(a)), and vehicle fleet breakdown by vehicle age in China (Figure S5(b)), we first estimate the annual average VKT using Equation (S5); the relationship between annual VKT and car ownership level is then determined and shown in Figure S5(c).

$$GC_{CY} = \sum_{MY} FC_{MY} \times VS_{CY} \times Comp_{MY,CY} \times VKT_{CY} \qquad \text{(S5)}$$

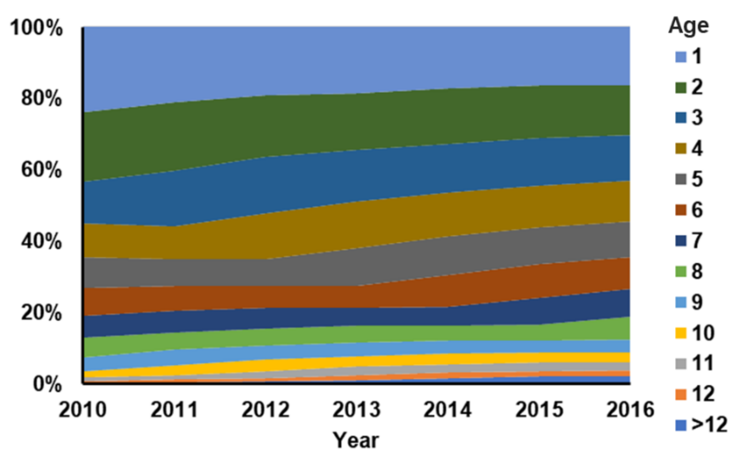
Where GC_{CY} is gasoline consumption by private passenger cars in calendar year CY (L); FC_{MY} is the on-road fuel consumption rate of cars with model year MY (L/km); VS_{CY} is vehicle stock in calendar year CY (#); $Comp_{MY,CY}$ is fleet composition by age (or by model year MY) in calendar year CY (%); VKT_{CY} is the annual vehicle kilometer traveled in calendar year CY (km).

Note that we fit a power law to the estimated VKT only from 2013 to 2016 (shown in a red line) because those VKT estimations before 2013 are very uncertain due to the limited and sparse data on fuel consumption and vehicle sales in the earlier years. The results show that the annual VKT of private cars would decrease gradually toward the future when the car ownership level is increasing, which is consistent with other national and city VKT survey studies [24–27].

(a)



(b)



(c)

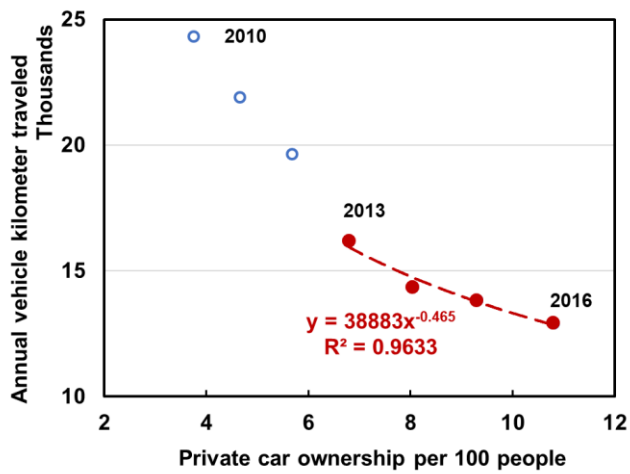


Figure S5. (a) Labeled and real-world fuel consumption rates for private vehicles in China with different model year; (b) private vehicle fleet breakdown by vehicle age; (c) estimated annual vehicle kilometer traveled (VKT) and the derived relationship between VKT and vehicle ownership level (in red line).

Based on the obtained equation (shown in Figure S5(c)), we further estimate the VKT at the provincial level based on the provincial vehicle ownership level, as shown in Figure S6.

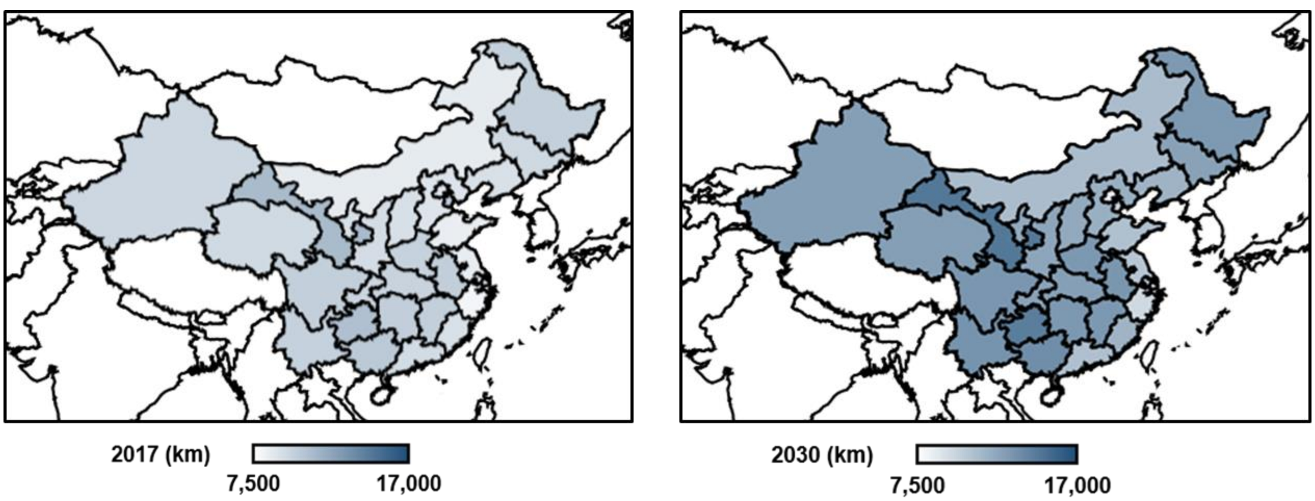


Figure S6. Annual vehicle kilometer traveled in 2017 and 2030 in the provinces of China modeled in the present work. ***Note: GeoNames[17] is used for data visualization and only the provinces of China modeled in the present work are shown using colors in the figure.***

6. Emission factors (EFs)

6.1 Well to tank (WTT): Electricity generation carbon emission factor

The scale of China's power grids has been expanded from small urban power grids, provincial power grids, and regional power grids to interconnected national power grids. Energy resource distribution in China is geographically unbalanced: ~85% of coal reserves are in the seven provinces (north and northwest) [28]; ~70% of exploitable hydropower are concentrated in the southwest [29].

Figure S7 presents the impacts of this inter-provincial transmission on the provincial grid carbon emission factor in 2017, categorized by the regional power grids. The simple carbon emission factors (EFs) refer to the EFs without considering the electricity transmission among provinces, which are calculated using the methodology proposed by National Development and Reform Commission (NDRC) in China[30]. On the other hand, the grid EFs not only take the emissions from power generations within the region but also the emissions from other regions via interregional electricity trading. The data of electricity generation from different types of generators are drawn from China Electric Power Yearbook (2018)[31]. The data of interregional electricity trading are obtained from China Electricity Commission CEC (2018)[32].

Carbon intensities of grids are found to be noticeably different in Beijing, Chongqing, Shanghai, and Guangdong between ones with and without considering the transmission. Collectively, Beijing, Shanghai, and Guangdong accounted for 46% and 33% of China's EV sales in 2016 and 2017. This implies that ignoring the electricity transmission might result in the wrong conclusions when examining the benefits of EVs in terms of climate change mitigation.

For the future carbon intensity of the electricity sector in the renewable energy expansion case (i.e., *EV-REN SCENARIO*), we follow the expected decarbonization rates at regional level that were documented in Shen et al. [33]. Shen et al. provided a projection of 2030 energy structure transformation of regional power grids based on China's ongoing large-scale construction of non-fossil electricity capacity and the released five-year and long-term plans; the inter-regional transmission capacity was also considered in Shen et al. The expected CO_2 reduction rates that are applied in *EV-REN SCENARIO* are shown in Table S5.

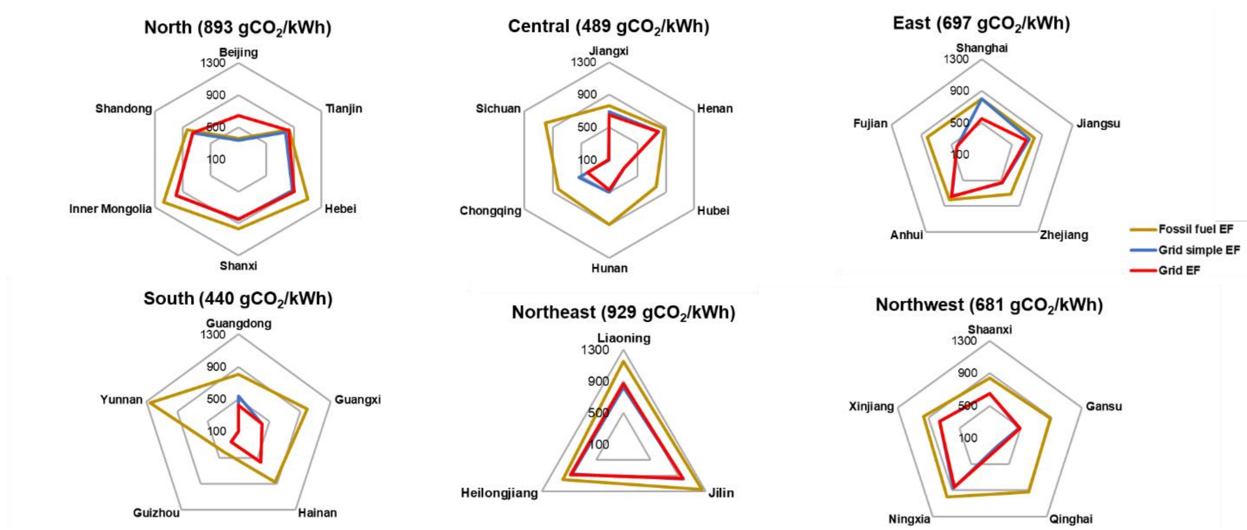


Figure S7. Carbon dioxide emission factors (EFs) for Chinese province electricity generation in 2017, categorized by regional power grids; red lines represent CO_2 EFs considering inter-provincial power flows, while blue lines denote simple CO_2 EFs which do not consider interregional electricity trading; EFs of local fossil fuel power plants are also presented (in yellow) here for reference.

Table S5. Improvement rates of power grid's carbon emission factor by region applied in *EV-REN SCENARIO* based on Shen et al. [33]

Province	2030/2017 EF_{CO2} ratio
Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Shandong	0.684
Liaoning, Jilin, Heilongjiang	0.667
Shanghai, Jiangsu, Zhejiang, Anhui, Fujian	0.761
Jiangxi, Henan, Hubei, Hunan, Chongqing, Sichuan	0.869
Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang	0.880
Guangdong, Guangxi, Guizhou, Yunnan	0.820

6.2 WTT: Electricity generation air pollutant emission factor

In a recent study by Tang et al. [34], researchers found that between 2014 and 2017 China's annual thermal power emissions of SO_2, NO_x, and PM dropped substantially thanks to the introduction of ultra-low emissions (ULE) standards policy in 2014. The researchers estimated emissions using continuous monitoring systems network, which covered most of the Chinese thermal power capacity, to be up to 92% below other recent estimates. The most disaggregated data Tang et al. [34] provided are at regional level, and since we do not have their study's full dataset, here we assume that every province belonging to the same region has the same emission factors for the thermal power plants. On the other hand, air pollutant EFs for renewable energy power plants are set to be zero. Then, based on Tang et al.'s thermal power EFs[34] and the renewable power capacity, we compute the capacity-weighted average air pollutant EFs at provincial level. Air pollutant EFs of electricity generation remain unchanged from 2017 to 2030 in *EV SCENARIO*.

On the other hand, in the renewable energy expansion case (i.e., *EV-REN SCENARIO*), both the increasing ULE compliance rate and expanding renewable energy are taken into account: 1) ULE compliance: Based on the historical data given in Tang et al. [34], we construct the relationship between emissions and the ULE compliance rate, as shown in Figure S8 (points are historical data). Since the eastern, northern, central and southern regions (collectively account for 74.4% of the total national power capacity in 2017) faced the most considerable pressure for emission reductions, the ULE policy prioritized them over the other regions in terms of timelines. And because the eastern, northern, central and southern regions also face the toughest policy stringency, we expect and assume that their thermal power plants will 100% meet the ULE standards by 2030. In order to meet the nationwide 2030 target of 90% ULE compliance rate, the rest three regions (northeast, southwest, and northwest) should at least achieve 60% compliance rate; we therefore assume their thermal power plants will 60% meet the ULE standards by 2030. 2) Renewable expansion: we follow the reduction rates of the share of combined fossil fuel in the power generation mix at regional level documented in Shen et al.[33]. The resulting 2030 air pollutant EFs used in *EV SCENARIO* (i.e., same as 2017 EFs) and *EV-REN SCENARIO* in this study are summarized in Table S6. We convert PM to $PM_{2.5}$ based on the satellite-based observation that PM contains about a 46% mass fraction of primary PM2.5 in China's power plant emissions[35]. Scenario and sensitivity analysis are conducted to study how our results change to the uncertainties in these emission factors (Supplementary Information 9).

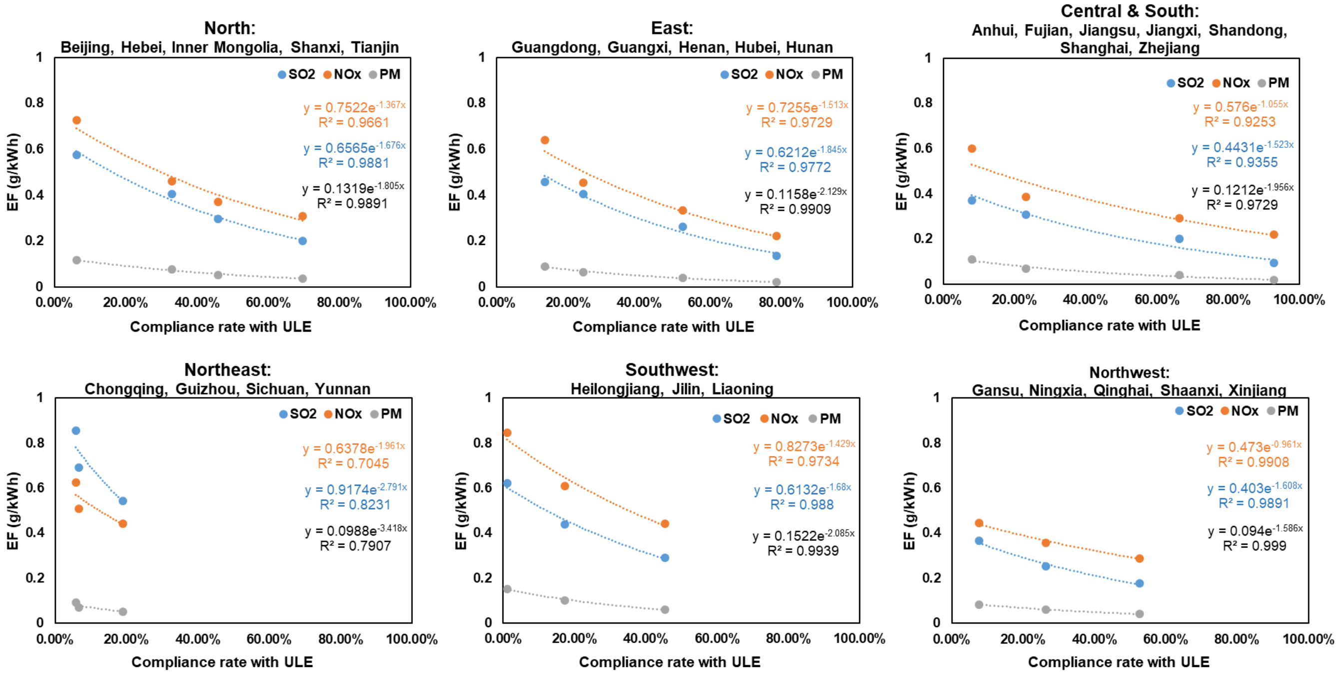


Figure S8. The relationship between air pollutant emission factors and ultra-low emissions standard (ULE) compliance rate by regions.

Table S6. 2030 air pollutant emission factors (EFs) used in *EV SCENARIO* and in *EV-REN SCENARIO* in the study.

2030	EV SCENARIO			EV-REN SCENARIO		
(g/kWh)	NO_X	$PM_{2.5}$	SO_2	NO_X	$PM_{2.5}$	SO_2
Beijing	0.234	0.013	0.152	0.108	0.006	0.069
Tianjin	0.271	0.015	0.176	0.125	0.007	0.080
Hebei	0.199	0.011	0.129	0.092	0.005	0.059
Shanxi	0.238	0.013	0.155	0.110	0.006	0.070
Inner Mongolia	0.210	0.012	0.137	0.097	0.005	0.062
Liaoning	0.291	0.018	0.192	0.155	0.009	0.099
Jilin	0.263	0.016	0.173	0.140	0.008	0.089
Heilongjiang	0.306	0.019	0.201	0.163	0.009	0.104
Shanghai	0.199	0.008	0.085	0.148	0.006	0.069
Jiangsu	0.170	0.006	0.072	0.126	0.005	0.059

Zhejiang	0.146	0.006	0.062	0.109	0.004	0.050
Anhui	0.160	0.006	0.068	0.119	0.005	0.055
Fujian	0.140	0.005	0.059	0.104	0.004	0.048
Jiangxi	0.144	0.005	0.061	0.116	0.005	0.054
Shandong	0.172	0.007	0.073	0.117	0.005	0.054
Henan	0.180	0.008	0.110	0.114	0.005	0.070
Hubei	0.082	0.004	0.050	0.052	0.002	0.032
Hunan	0.122	0.005	0.075	0.077	0.003	0.047
Guangdong	0.160	0.007	0.098	0.098	0.004	0.060
Guangxi	0.110	0.005	0.067	0.067	0.003	0.041
Chongqing	0.330	0.018	0.405	0.129	0.004	0.113
Sichuan	0.062	0.003	0.076	0.024	0.001	0.021
Guizhou	0.248	0.013	0.304	0.094	0.003	0.082
Yunnan	0.088	0.005	0.109	0.034	0.001	0.029
Shaanxi	0.206	0.014	0.126	0.176	0.011	0.102
Gansu	0.119	0.008	0.073	0.102	0.006	0.059
Qinghai	0.045	0.003	0.028	0.039	0.002	0.022
Ningxia	0.164	0.011	0.100	0.140	0.009	0.081
Xinjiang	0.180	0.012	0.110	0.154	0.010	0.089

6.3 WTT: Emissions to produce gasoline

The emissions factors (EFs) of CO_2, VOC, NO_x, SO_2, $PM_{2.5}$ applied in this study are derived from Zheng et al.[36] and Ke et al.[37]. Zheng et al. provided 2015 WTT EFs for gasoline in China, and we estimate the following WTT EFs throughout 2030 using linear interpolation based on the Ke et al.'s projected improvement rates. The resulting 2017 and 2030 WTT EFs for gasoline used in *EV SCENARIO* and in *EV-REN SCENARIO* in this study are summarized in Table S7. Due to the lack of data, all provinces are assumed to have the same upstream WTT emissions for a liter of gasoline production.

Table S7. Emission to produce gasoline in China, i.e., upstream well-to-tank stage

g/L	CO2	CO	VOC	NOx	SO2	PM2.5
2017	899	0.630	1.02	2.06	0.94	0.14
2030	817		1.00	1.46	0.64	0.11

6.4 Tank to wheel (TTW): On-road energy consumption

The average label fuel consumption rate for new ICEVs and HEVs combined will achieve 5.8 L/100 km in 2020, 4.55 L/100km in 2025, and 4.0 L/100km in 2030[38]. The average label fuel consumption rate for new ICEVs and HEVs combined will achieve 5.8 L/100 km in 2020, 4.55 L/100km in 2025, and 4.0 L/100km in 2030[38]. The fuel consumption gaps between label and average on-road values for gasoline vehicles are assumed to remain at -26% out to 2030[39]; thus, the average on-road fuel consumption rate of new gasoline vehicles will be 5.0 L/100km (= 4.0 × 1.26) by 2030. Due to a lack of local car sales data by vehicle size, we assume that the average label fuel consumption in each province is the same as the national sales-average level. The historical sales-average label fuel consumption of ICEVs and BEVs in China are taken from multiple sources [8,40]. In 2017, the average label value of ICEVs is 6.7 L/100 km and that of BEVs is 15 kWh/100km. For BEV fuel consumption improvement, we take the projection from MIT On the Road Toward 2050 [6], suggesting that there will be a ~17% reduction in BEV fuel consumption from 2017 to 2030. We estimate sales-average PHEVs fuel consumption based on the reference vehicles' fuel consumption ratios (Table S1) between PHEV and ICEV (gasoline-powered PHEV fuel consumption is 21% lower than ICEV) and between PHEV and BEV (battery-powered PHEV fuel consumption is 29% higher than BEV).

The New European Driving Cycle (NEDC), the currently-used type approval cycle, is inconsistence with the characteristics of the actual driving condition in China, causing the fuel consumption gaps between lab and on-road values to become larger—the real-to-lab divergence for gasoline vehicles has increased from 12% in 2008 to 26% in 2016 [39]. Considering the more realistic testing cycle, the Worldwide harmonized Light vehicles Test Procedures (WLTP), will be implemented soon [41], we expect and assume the real-to-lab gap for gasoline cars would not increase further, and would instead remain 26% out to 2030. For battery-powered vehicles fuel consumption, we estimate the real-to-lab gap based on the difference in electric driving range between WLTP test and NEDC test for the same car model (i.e., Tesla Model 3 is chosen here), which is found to be 19%.

Driving conditions—such as weather, traffic, driver behavior, and fuel quality—affect fuel consumption significantly. Fuel consumption index was proposed to describe the real-world fuel consumption levels across provinces [42], showing that Heilongjiang and Jilin have the highest fuel consumption (~10% higher than the national average), while Yunnan has the lowest fuel consumption (~7% lower than the national average). Figure S9 shows the on-road fuel consumption of ICEV and HEV combined used in this study at provincial level in 2017 and 2030.

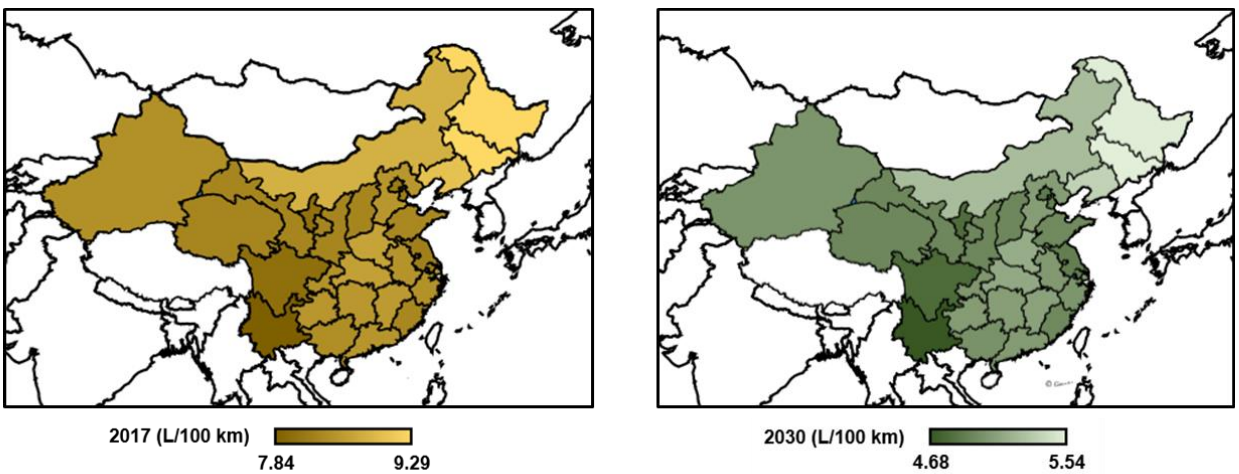


Figure S9. On-road fuel consumption of gasoline vehicle (ICEV and HEV combined) in 2017 and 2030 in the major Chinese provinces. ***Note: GeoNames[17] is used for data visualization and only the provinces of China modeled in the present work are shown using colors in the figure.***

6.5 TTW: On-road emissions from using gasoline

Carbon emission from using gasoline is assumed to be 75 gCO_2/MJ, derived from Yang et al. [43]. With the given on-road fuel consumption, we can compute the carbon emission per km driven at the provincial level. It is noted that the low heating value of gasoline is used in this study.

We derive provincial-level on-road air pollutant EFs based on a framework developed by Tsinghua University and the Chinese Academy of Environmental Sciences [44], as represented in Equation S6.

$$EF_{i,j} = BEF_i \times \delta_{i,j} \tag{S6}$$

$EF_{i,j}$ is the emission factor of air pollutant *i* in region *j*; BEF_i is the integrated base emission factor of air pollutant *i*; $\delta_{i,j}$ is the correction factor of temperature, humidity, altitude, driving speed, and oil quality in region *j*. All factors are summarized in Table S8. Unlike the previous fuel standards in China, China 6 does not only follow the basic European regulation system, but also goes beyond it in terms of emission stringency. It was expected that many automakers would be producing vehicles meeting California's LEV III light-duty vehicle emission standards for California market and thus could produce them much quicker than the China 6 in China [45]. EFs under China 6 are obtained from Ke et al. [37].

Table S8. Values of base emission factor (BEF), correction factor (δ), and on-road emission factor for different fuel standards, air pollutants, provinces for the gasoline vehicles

Fuel standard	**BEF (g/km)** CO	**VOC**	**NOx**	**$PM_{2.5}$×10**	**Implementation year** (BJ:Beijing; SH: Shanghai; GD: Guangdong)
China Pre 1	32.15	3.23	2.05	0.28	
China 1	11.61	0.91	0.41	0.26	BJ 1999; SH 2000; Nationwide 2001
China 2	2.6	0.48	0.43	0.11	BJ, SH 2003; Nationwide 2006
China 3	1.58	0.22	0.15	0.07	BJ 2006; SH, GD 2007; Nationwide 2009
China 4	0.69	0.08	0.03	0.03	BJ 2009; SH 2010; GD 2011; Nationwide 2012
China 5	0.46	0.06	0.02	0.03	BJ 2013; SH 2015; GD 2016; Nationwide 2017
Province	**δ** CO	**VOC**	**NOx**	**$PM_{2.5}$×10**	**Causes for correction**
Yunnan	2.15	3.62	3.62		Average temperature <10 °C & altitude>1500 m
Heilongjiang, Chongqing	1.36	1.47	1.15		Average temperature <10 °C
Qinghai	1.58	2.46	3.34	--	Average humidity <50 % & altitude>1500 m
Xinjiang	1	1	1.06		Average humidity <50 %
The rest	1	1	1		
Fuel standard	**EF (g/km)** CO	**VOC**	**NOx**	**$PM_{2.5}$×10**	**Implementation year**
China 6	0.23	0.02	0.01	0.02	BJ, SH 2018; GD 2019; Nationwide 2020

6.6 Cradle to gate: CO_2 emissions from vehicle and battery production

Several research studies analyzed the CO_2 emissions related to vehicle and battery production in China [1–5]. Based on the vehicle weights and battery capacity, we derive the reference vehicle-specific CO_2 emissions from manufacturing process in 2017 (Table S1). Due to the unavailability of data regarding manufacture-related emissions at the provincial level, we assume all regions across China have the same vehicle cycle emissions. For the future improvement (throughout 2030), we follow the CO_2 emission reduction rate given by Elgowainy, Amgad, et al. (2018) [46]: 12% for ICEV, 13% for HEV, 52% for EV battery, and 15% for EV components except for battery.

7. Air quality modeling and health concentration-response functions

China's gasoline refining process is using coal as the main process fuel, and in the absence of strict emission standards, substantial emissions are expected to be produced. Hence, this study considers the changes in emissions from gasoline production when computing air quality (besides the emissions from electricity generation and gasoline consumption). For spatial allocation of WTT emissions from ICEVs, we first calculate total fuel demand from the private vehicle sector in each scenario, and then multiplied it by the emission factor (g/L) shown in Table S7 to get the nationwide WTT emissions from gasoline production; we then allocate the total national emissions based on the location (latitude/longitude) and the capacity volumes of the gasoline refineries[47].

For each scenario, projected annual power generation and passenger car emissions of CO, NO_x, VOC, SO_2, and $PM_{2.5}$ in 2030 are estimated at the province-level. For each province, these sectoral totals are disaggregated by month following the temporal pattern observed in the 2016 MEIC inventory [48]. This assumes that the temporal profile of power and road transportation emissions will remain constant by 2030. In addition, projected emissions are also assumed to follow the same spatial pattern as the corresponding sectors in the MEIC inventory[48]. We further disaggregate VOC emissions by species (considering formaldehyde, ethane, propane, alkanes with 4 or more carbon atoms, acetone, acetaldehyde, methyl ethyl ketone, and alkenes with 3 or more carbon atoms) according to their respective share in the total VOC emissions in the 2016 MEIC inventory. Anthropogenic emissions other than passenger car emissions and power emissions related to the deployment of EVs are taken from the MEIC inventory [48] and scaled up from 2016 to 2030 on a monthly basis according to the projections by pollutant and province obtained from the GAINS China model [49,50] with the World Energy Outlook (WEO) New Policies Scenario [50] which assumes the full implementation of current legislation. In this work we focus on the policy impacts on 29 administrative units (or provinces) of China, while the air quality model includes meteorological conditions over these and all the other units and a large portion of East Asia. Emissions from other countries within the geographic domain are treated as constant over the period of study and taken from the CEDS global inventory[51,52].

Monthly emissions derived from the MEIC and CEDS emissions inventories are then input into the GEOS-Chem air quality model. The GEOS-Chem air quality model is run at a 0.5°×0.625°

resolution of over East Asia (about 320200 grid cells, including 133145 cells over China) with 47 vertical layers up to an altitude of 80 km. The boundary conditions for this domain are obtained using a global 2°×2.5° simulation. For each scenario, the model is run over a 15-month period, and we calculate results using the final 12 months.

Surface-level concentration of $PM_{2.5}$ and ozone are then combined with population data to estimate exposure. Total population by province for the base year 2017 is taken from the China Statistical Yearbook [53]. Population growth by 2030 is from the UN World Population Prospects [54], and inter-provincial migration flows are estimated following the method described in Supplementary information 4.1.3. The spatial distribution of population within each province is taken from the Global Human Settlement Layer developed by the EU Commission's Joint Research Center [55] and is assumed to remain constant between 2015 and 2030. The population age structure in 2017 is taken from WHO data [56] and also assumed to remain constant by 2030. Mortality impacts are calculated for the fraction of population aged 30 and above.

The baseline incidence rates in China for 1) the mortality health endpoints considered for $PM_{2.5}$ and ozone are taken from the Global Burden of Disease Study 2015[57]; 2) the $PM_{2.5}$-related morbidity health endpoints are taken from Maji et al.[58]; 3) the ozone-related morbidity health endpoints are taken from Feng et al.[59]. For each health endpoint, the relative risk for each age group is related to the number of premature mortalities following the well-established method[60–62] of the population-attributable fraction in each grid cell:

$$M_{d,a} = P_a \times B_{d,a} \times \frac{RR_{d,a}-1}{RR_{d,a}} \tag{S7}$$

where $M_{d,a}$ is the number of premature mortalities from endpoint *d* and age group *a* in a given grid cell, P_a is the population in the age-group in that grid cell, $B_{d,a}$ is the baseline incidence, and $RR_{d,a}$ is the relative risk obtained using the concentration-response functions described below.

The mortality impacts associated with changes in exposure to $PM_{2.5}$ across China are estimated using the Global Exposure Mortality Model [63]. The model relates the relative risk (RR) to the $PM_{2.5}$ concentration according to the following relation:

$$RR(z) = \exp[\theta \log(z/(\alpha+1)/\exp(-(z-\mu)/\upsilon], \textit{ where } z=max(0, c\text{-}2.4) \tag{S8}$$

with c the concentration of $PM_{2.5}$ in $g.m^{-3}$ in each grid cell. The parameters θ, α, μ, υ are defined for each 5-year age bracket between 30 and 85 years and for each of the following health endpoints: ischaemic heart disease, stroke, chronic obstructive pulmonary disease (COPD), lung cancer, and lower respiratory infection. Using the distributions for each of these parameters provided in Burnett et al. [63], we generate 10,000 independent samples of the health impacts related to changes in concentrations of $PM_{2.5}$.

For mortality impacts due to changes in surface-level ozone, we apply a log-linear concentration-response function, using parameters derived from Turner et al. [64]. This function relates exposure to 8-hour maximum ozone concentration (MDA8) to premature mortality from respiratory and circulatory diseases. The reported central relative risk for circulatory diseases is 1.03 (95% CI: 1.01 to 1.05) and the central relative risk for respiratory diseases is 1.12 (95% CI: 1.08 to 1.16) for a 10 ppb increase in ozone MDA8. We generate 10,000 independent samples of each of these parameters using a triangular distribution fitted to the reported modes and values. Each of these samples translates to a sample of the parameter and we estimate the relative risk under each scenario in each grid cell using the following formula:

$$RR(z) = \exp(\beta z), \textit{ where } z=\max(0, c-35) \tag{S9}$$

with c the ozone MDA8 in ppb, and 35 ppbv the threshold suggested by Turner et al. [64]. Based on the data reported in the original study, we estimate central a value of 0.00296 for β for circulatory diseases, and 0.0113 for respiratory diseases. The health endpoints considered include ischemic heart disease, stroke, chronic obstructive pulmonary disease (COPD), lung cancer, and lower respiratory infection.

In addition to premature death, for each scenario, we also quantify the morbidities caused by PM2.5 and ozone exposure in 2030. Five PM2.5-related morbidity health impacts (including hospital admission due to respiratory disease (RHA), hospital admission due to cardiovascular disease (CHA), chronic bronchitis (CB), asthma attack (AA) and emergency room visits (ERV) for respiratory disease) and two ozone-related morbidity health impacts (including RHA and AA) among all ages are calculated using Equation S9; exposure-response coefficients (ER) coefficients and the threshold (i.e., c_0=10 μg/m^3 for PM2.5 and 35 ppb for ozone) are taken from Maji, Kamal Jyoti, et al and Feng, Zhaozhong, et al studies [58,59].

$$RR(z) = \exp[ER \times (c - c_0)] \tag{S10}$$

8. Economic benefits and transition costs

8.1 Economic benefits

To facilitate comparisons with the financial costs, the benefits of climate and health stemming from EV policies (including the introduction of tighter emission standards and the adoption of energy-saving and new energy vehicles) are quantified in terms of the economic values of CO_2 emission reduction and avoided health endpoints. All economic numbers in this paper are given in 2017 Yuan. Note that there is significant uncertainty and controversy on how to appropriately value human health/life and environmental benefits in monetary terms; see e.g., Viscusi and Aldy (2003)[65] and Ricke et al. (2018)[66].

The key assumption of benefit-transfer approach[67] is that people with higher incomes are willing to pay more to reduce their health risks. The province-specific health costs ($HC_{2030,p}$) values are estimated using Equation (S11), where HC_{base} is the base value. For mortality ($\mathrm{HC} = \mathrm{VSL}$), we take the most recent local VSL estimation that was provided by a contingent valuation study performed in Chengdu, China in 2016 as the baseline[68]; the suggested VSL is 3.85 million Yuan[2] with the disposable income ($Income_{2016,base}$) of 36,500 Yuan. For morbidity ($\mathrm{HC} =$ WTP or COI), we take the estimated health costs for Beijing or a national average in China given by Maji et al.[58]. Mean per capita disposable income for 2030 in each province ($Income_{2030,p}$) is discussed in Section 2.2. This study uses a 0.8 value of income elasticity of health cost as the base case as recommended by OECD [70], and examines the uncertainty in health benefits by using different income elasticities of health cost—ranging from 0.4[71] to 1[72].

$$HC_{2030,p} = HC_{base} \times \left(\frac{Income_{2030,p}}{Income_{2016,base}}\right)^{0.8} \tag{S11}$$

The climate change benefits and health benefits stemming from *EV SCENARIO* (relative to *EV-REN SCENARIO*) are quantified in terms of the economic values of avoided premature death, avoided morbidity cases, and climate change mitigation[3]. Here we have not attempted to quantify many other benefits of China's EV policy, e.g.:

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[2] This VSL obtained from Chengdu experiment is comparable to the other study conducted in Beijing in 2016[69].

[3] As discussed earlier, this paper quantifies the benefits due to the changes in total life cycle CO2 emissions and the changes in WTW air pollutants emissions under the current policy mix relative to no EV policy scenario.

1) Other benefits of reduced air pollution including quality of life
2) Other benefits of improved health besides premature deaths
3) Improved energy security due to reduced petroleum imports
4) More favorable balance of trade
5) Reduced congestion and traffic fatalities due to fewer cars.
6) Reduced land use for parking
7) Increased employment (e.g., in BEV factories, installation of EV charging infrastructure)
8) Forcing down worldwide BEV prices, leading to reduced global CO2 emissions.

8.2 Transition costs

Transition cost to society has been recognized as part of societal costs during the transition to electromobility owing to the incremental societal costs of ICEVs over EVs, including vehicle, replacement battery, infrastructure, and fuel/electricity costs. (Note that the societal costs can be large even if taxes, subsidies, and mandates make the two vehicle types about equally expensive to a consumer.[7]) For "costs" defined in this study, we follow the definitions provided in the previous study (see Reference 7): the system boundary of cost to society is limited to the car's purchase and uses themselves, including fuel/electricity consumption, insurance, maintenance, and battery replacement; all the taxes- and incentives-related terms are excluded from the calculations since they are just a redistribution within China instead of cost to society as a whole.

Spreading the capital costs over the vehicle lifetime, the computed direct economic cost to society of using the more expensive electric vehicles has been estimated at about 152 billion Yuan in 2030[4]. Note that this just counts direct costs; some of the costs/disadvantages of this policy are outside the study's scope, e.g.:

1) Loss of personal mobility in China due to many fewer private cars.
2) Associated loss in productivity due to increased travel time.
3) Energy insecurity due to imports of cobalt and lithium for batteries.

[4] Transition costs associated with vehicle purchase and battery replacement have been averaged out across the lifetime of the vehicle. Here, we focus on the direct economic costs corresponding to the on-road total km driven in 2030. Note that the cost-to-society values of vehicle purchased between 2021 and 2029 have been converted to the value in 2030, using the discount rate of 5%. Take vehicle purchased in 2028 as an example, society would pay two years earlier for the 2028 cars, so it could not earn interests on the cash like it does for the 2030 cars.

9. Sensitivity analysis

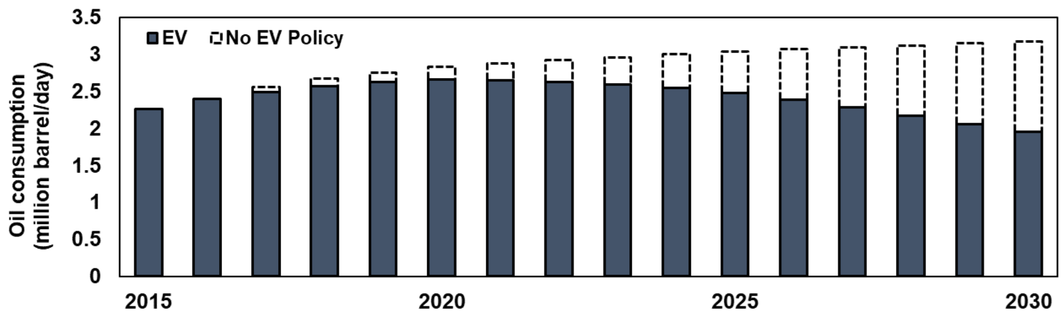
Table S9. Scenarios definition

Scenario	Definition
No EV Policy (Counterfactual)	Private car market size projection without EV mandates and quota policy (i.e., 385 million cars in 2030); 100% of private cars are ICEV even in 2030; on-road vehicle tailpipe emission factors (China 5 standard), fuel consumption rates, air pollutant emission factors for the power plants, and carbon emission intensity of the electricity generation stay the same after the base year 2017.
Fewer car	All the emission factors are the same as *No EV Policy* scenario; the only difference is in the projected private car market size. In the *Fewer car* scenario, car market size projection considers the car demand decrease due to the EV mandates and city-level quota policy (i.e., 302 million cars in 2030); but no EVs.
Cleaner ICEV/HEV	Car market size is 302 million in 2030; 100% of private cars are powered by gasoline complying with China 6 emission standards and having higher fuel efficiency (i.e., the average label fuel consumption rate for new ICEVs and HEVs combined will achieve 4.0 L/100km in 2030, same as *EV* scenario).
EV	In 2030: car market size is 302 million; the average label fuel consumption rate for new ICEVs and HEVs combined is 4.0 L/100km; EV sales market share is 37%; the provinces that are currently leading the national EVs sales will continue to dominate (see Supplementary Information 3); all the emission factors for the power plants stay the same after the base year.
EV-Homo	All the conditions are the same as *EV* scenario except for the geographical patterns of future EV population growth. *EV-Homo* scenario assumes all provinces are having the 37% EV sales market share in 2030 (i.e., homogeneous EV penetration pattern across China).
EV-Double	All the conditions are the same as *EV* scenario except for the future EV penetration rate. *EV-Double* scenario assumes 74% (= 37% × 2) EV sales market share in 2030.
EV-REN	All the conditions are the same as *EV* scenario except for the future power grid emission factors. *EV-REN* scenario is designed to have the improving carbon and air pollutant emission intensity of the power grid: by 2030, the carbon intensity of the power grid at the national level is projected to decrease to 464 gCO2/kWh and the nationwide target of 90% ULE standards compliance rate is achieved.

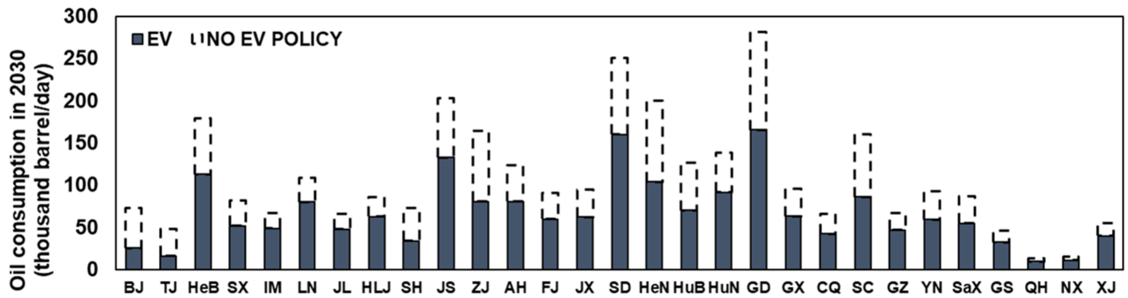
10. Supplementary figures

Figure S11. Comparison between No EV Policy Counterfactual Scenario and EV Scenario in the major Chinese provinces. (a) Annual total amount of gasoline consumption for the private vehicles from 2015 to 2030[5]; (b) 2030 gasoline demand from the private vehicle sector at the provincial level; (c) annual nationwide life cycle CO_2 emission in China from 2015 to 2030.

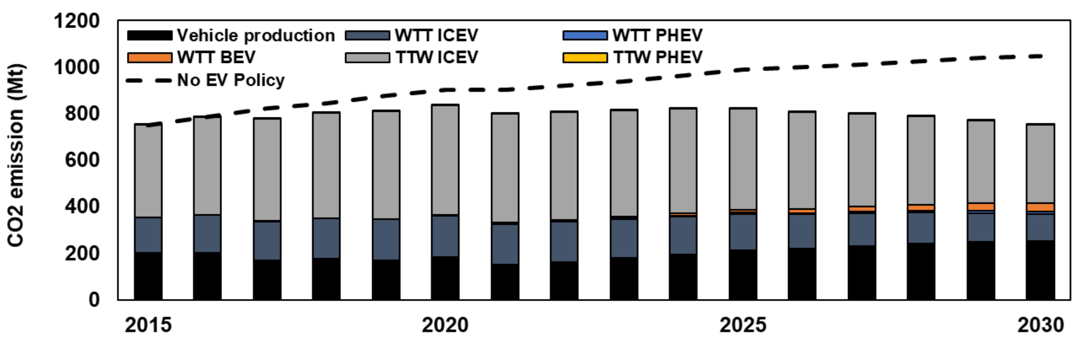
(a)



(b)



(c)



[5] Assuming 0.177 tons of gasoline are obtained from 1 ton of crude oil, we estimate that about 19% of China's total oil consumption in 2018 was from private vehicles. Moreover, the annual gasoline demand from the private vehicle sector is expected to peak in 2020; this is mainly because of the decreasing vehicle use intensity (Supplementary Information 4.5) and the temporary car market contraction due to the removal of EV subsidies.

Figure S12. Annual amount of CO, VOC, NOx, SO2, and primary PM2.5 emissions from the WTW stage of the private cars for No EV Policy Counterfactual Scenario and EV Scenario in China from 2015 to 2030.

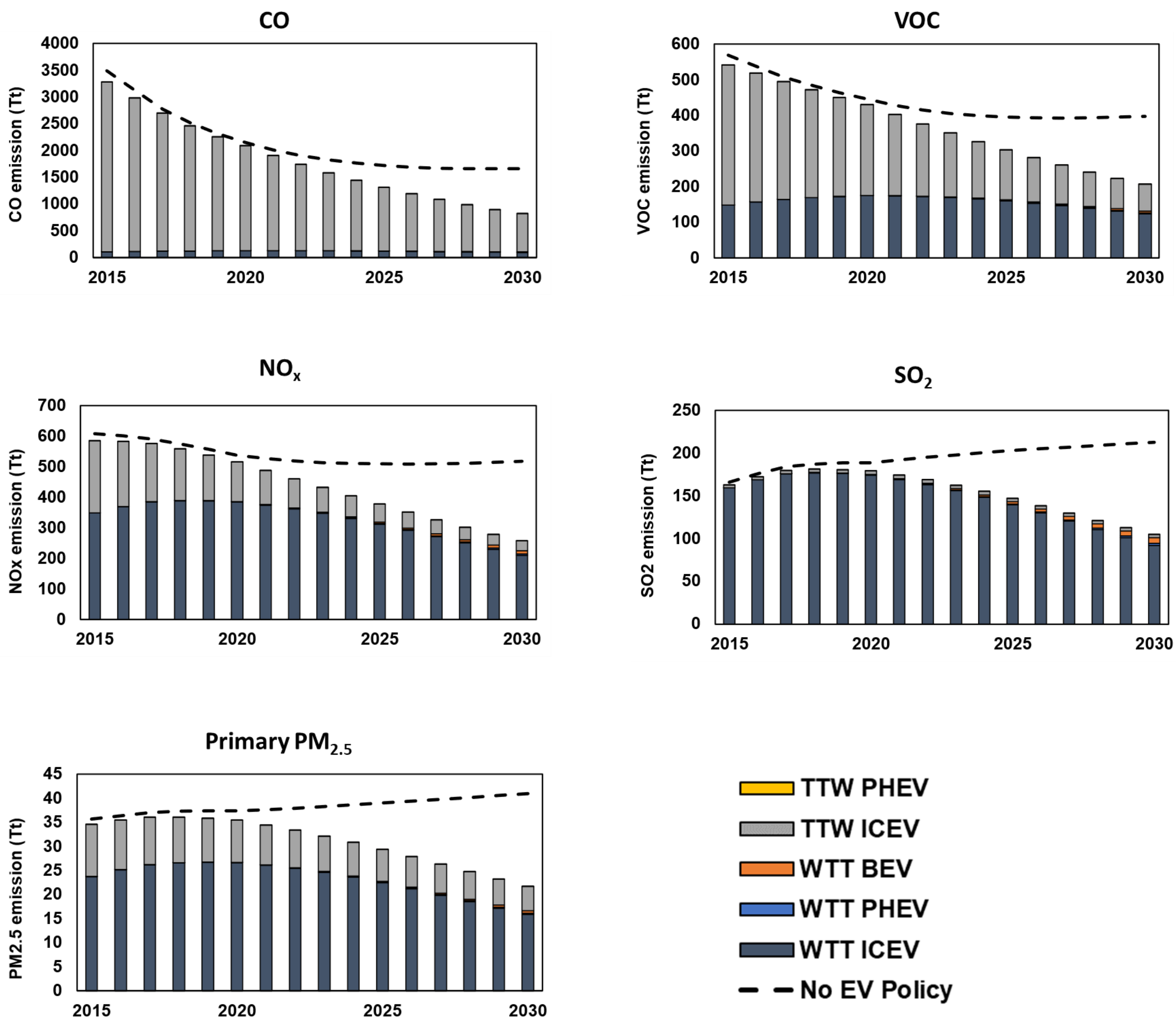


Figure S13. Economic benefits of air quality-related health benefits and life-cycle CO_2 emissions in *EV SCENARIO* compared with *NO EV COUNTERFACTUAL SCENARIO* at provincial level in China, 2030. The intervals for monetary benefits of air quality benefits are derived using the income elasticity of 0.4 and 0.1 (the base case in this study is 0.8); the intervals for economic benefits of life-cycle CO_2 emissions are estimated using US$4 per tCO_2 and US$50 per tCO_2 (the base case is US$24 per tCO_2).

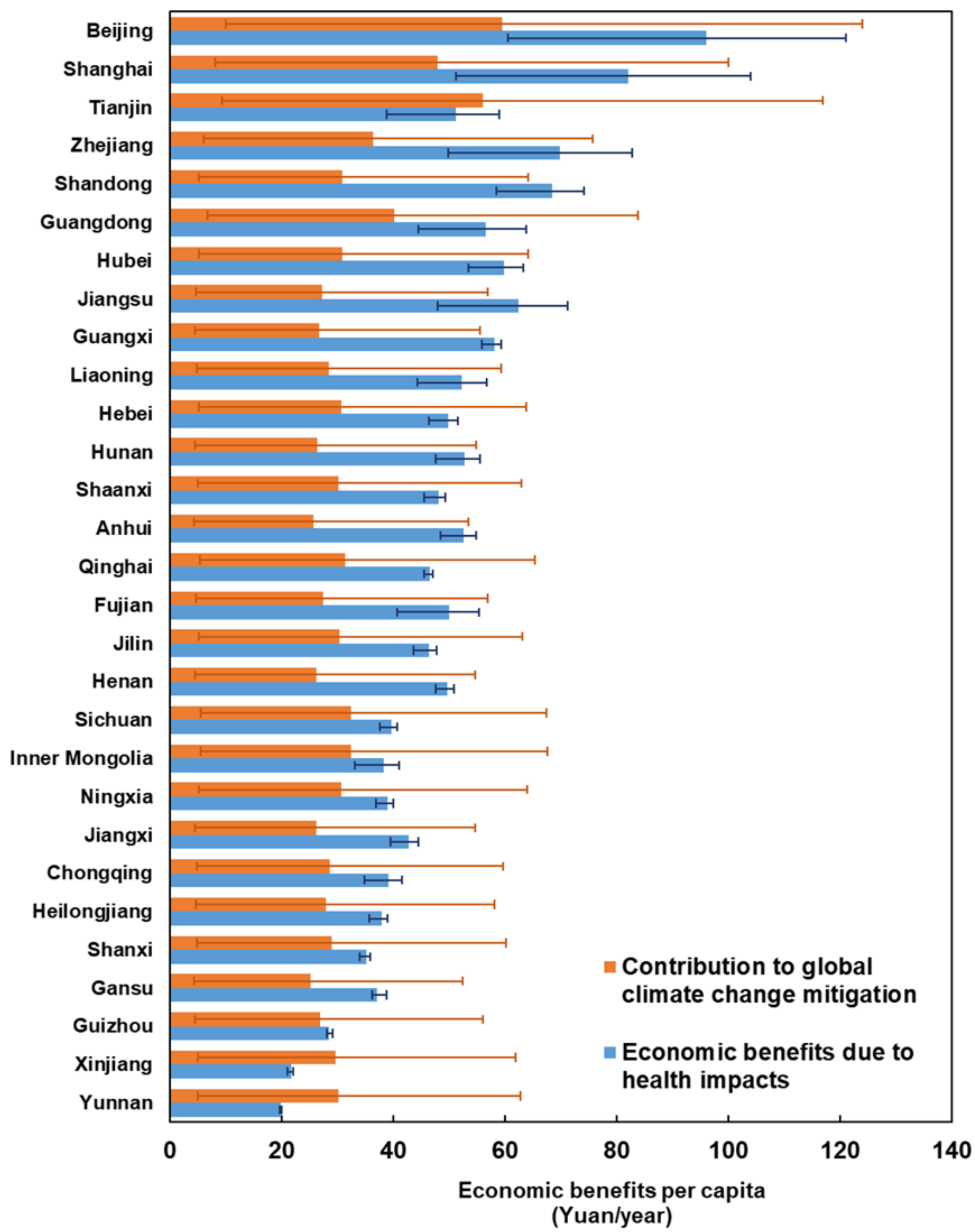
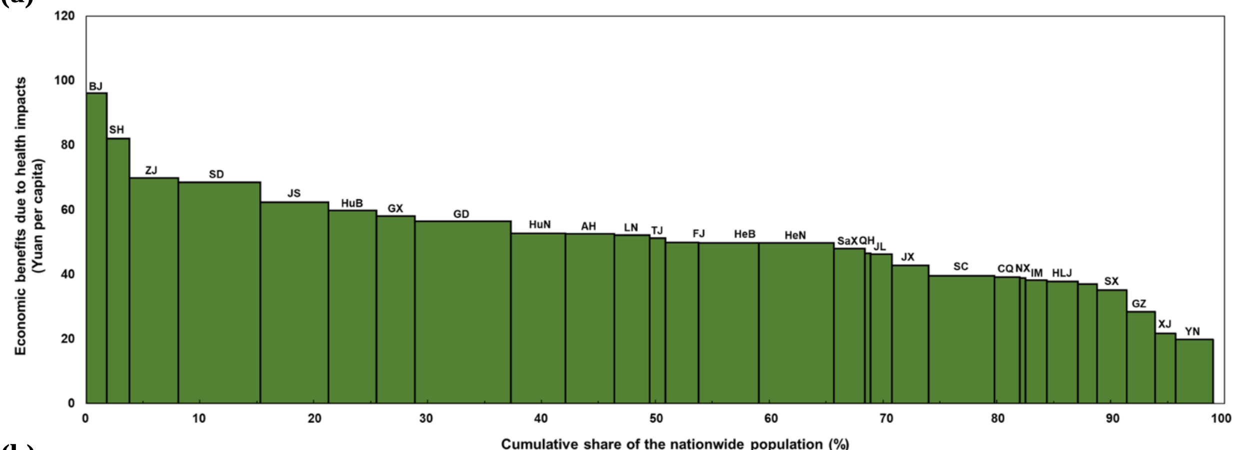
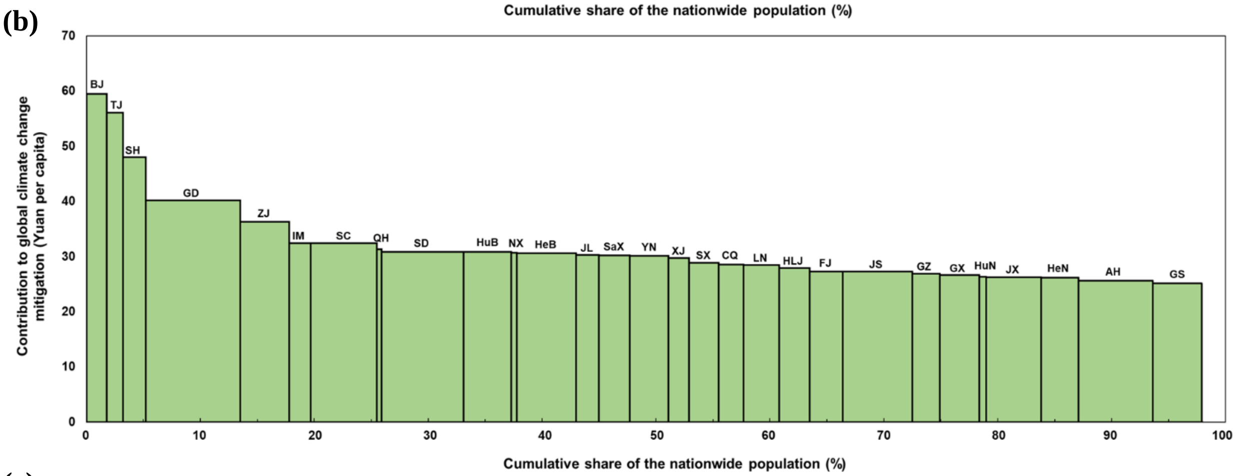


Figure S14. Distribution of total economic benefits and costs associated with EV policy by province in 2030, in descending order: (a) health benefits due to reduced air pollution; (b) contribution to global climate change mitigation benefits; (c) transition cost to society. Per capita value on y-axis; percentage share of mainland China's total population (1.42 billion) on x-axis; the area of each rectangle is proportional to the total value of the benefit, contribution, or cost associated with that province. This study captures 99% of the population of mainland China (Hainan and Tibet are excluded).

(a)



(b)



(c)

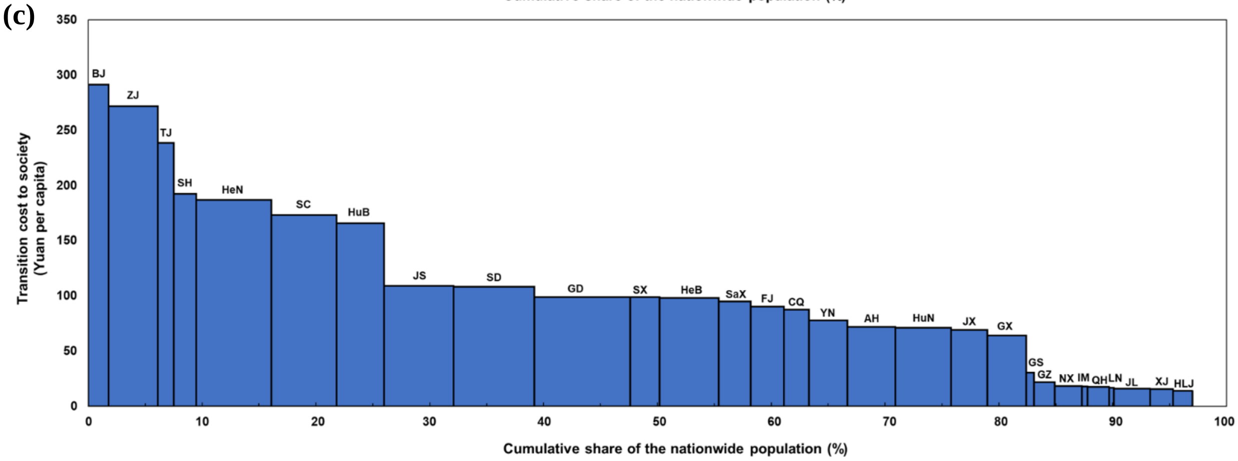
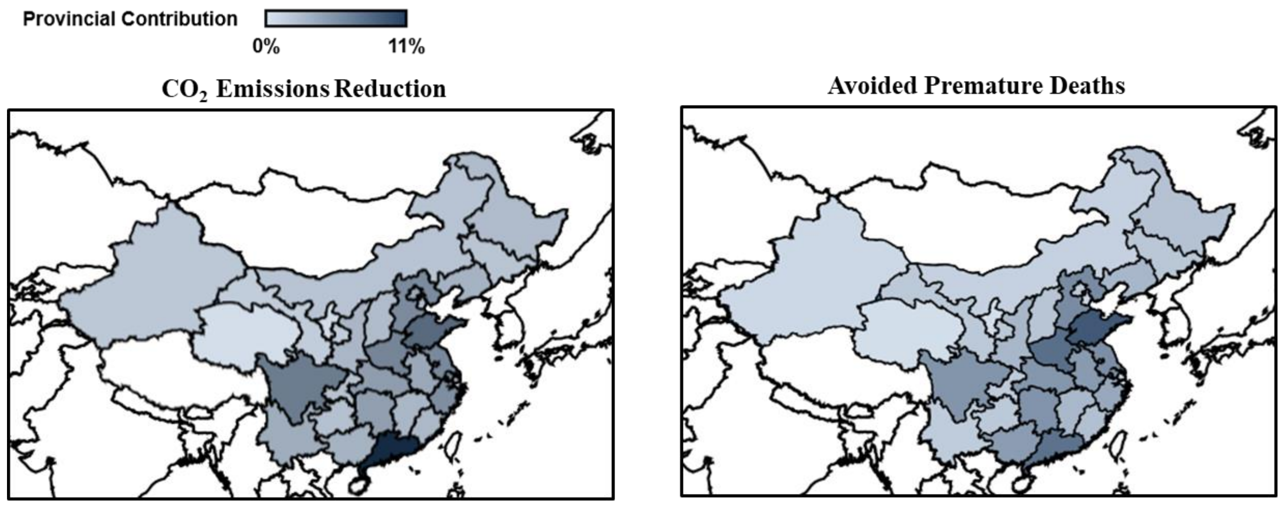
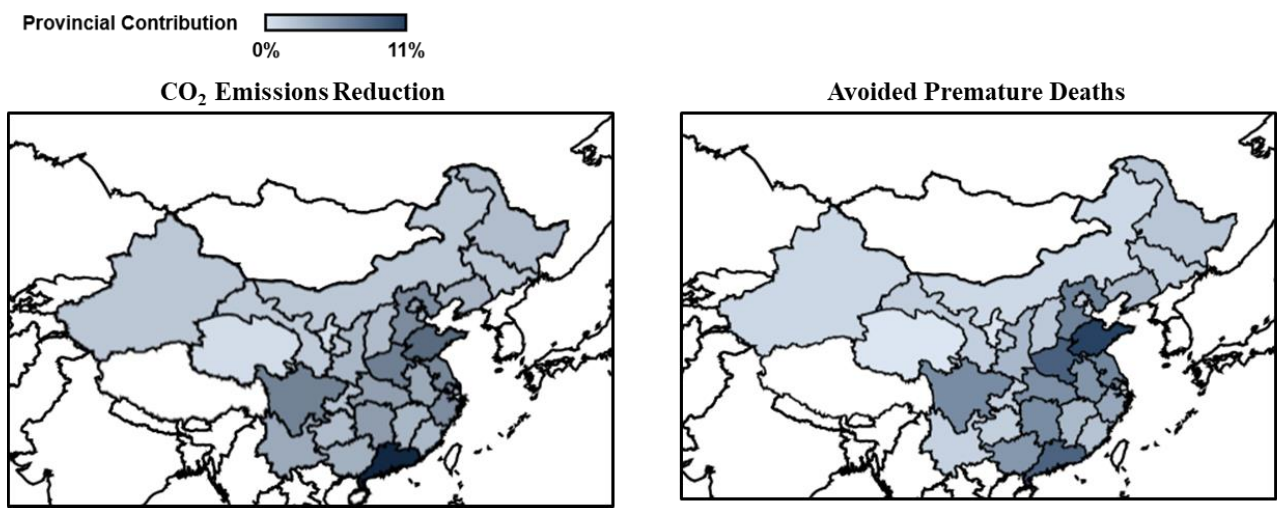


Figure S15. Provincial contribution to the total CO_2 emissions reduction and avoided premature deaths in (a) *EV Scenario* and (b) *EV-REN Scenario* compared to *No EV Policy Counterfactual Scenario*. *Note: GeoNames[17] is used for data visualization and only the provinces of China modeled in the present work are shown using colors in the figure.*

(a)



(b)



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