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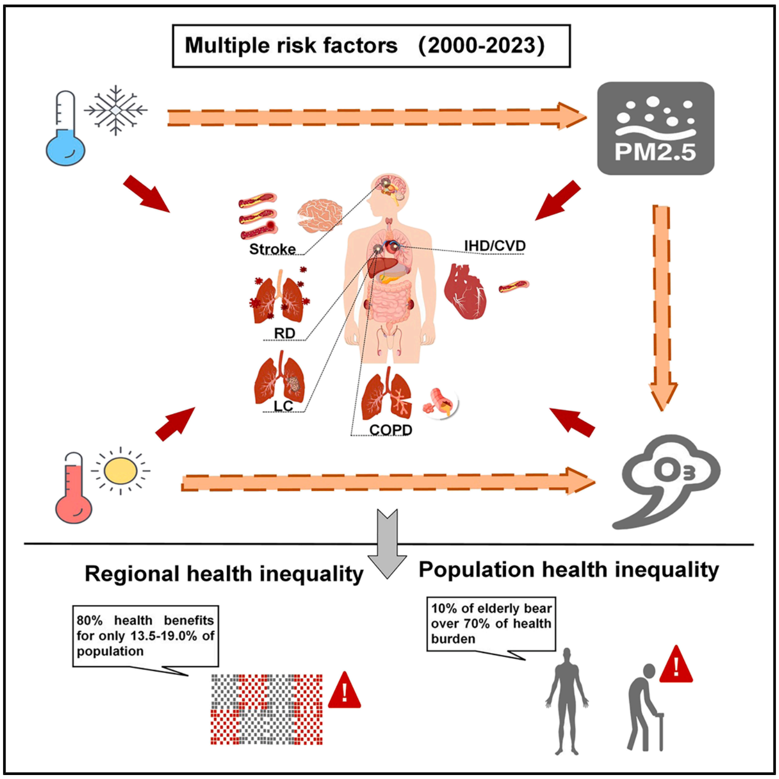
Air pollution and climate change drive health inequities across China's provinces (2000–2023)

Graphical abstract



Highlights

- Assessing multi-risk factors from long and short exposures
- 80% health benefits for only 13.5%–19.0% of population
- 10% of elderly bear over 70% of health burden
- Aging, healthcare gaps, climate vulnerability drive multi-risk inequalities

Authors

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In brief

Health sciences; Environmental health; Pollution

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Air pollution and climate change drive health inequities across China's provinces (2000–2023)

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SUMMARY

Achieving health equity is a key mission of the United Nations Sustainable Development Goals (SDGs). This study integrated epidemiological models for both acute and chronic health outcomes with climate, demographic, and cause-specific mortality data. It assessed province-level health inequalities and their drivers across China (2000–2023), focusing on short- and long-term exposures to air pollution ($PM_{2.5}$, ozone) and climate-related events (heatwaves, cold spells). The results show that China's clean air initiatives have significantly reduced $PM_{2.5}$ levels, improving short-term exposure risks and narrowing ozone-related health inequalities. However, densely populated and aging regions in northern and central China continue to bear disproportionate health burdens. A hidden inequality also emerges in the west, where low mortality counts mask high mortality rates. Approximately 80% of the health benefits accrue to just 13.5%–19.0% of the population, while older adults – only 10% of the population—bear over 70% of the health burden. The analysis identifies three key drivers contributing to health inequality: accelerated population aging, inequities in healthcare access, and heightened vulnerability to climate change. The multi-risk factor analysis reveals persistent significant inequalities in health risks and benefits across regions and demographic groups.

INTRODUCTION

The United Nations Sustainable Development Goals (SDGs) are committed to advancing health equity, but progress is hindered by disparities in exposure to air pollution (SDG 3.9) and climate change (SDG 13) driven by socioeconomic inequality. Since 2013, China has implemented its most stringent clean air action policy, with the two phases of the policy, phase I (2013–2017) and phase II (2018–2020), significantly reducing $PM_{2.5}$ concentrations.[1] However, societal changes, such as accelerating population aging, have offset the health benefits from air quality improvements, resulting in no significant decline in premature deaths.[2,3] Meanwhile, despite the implementation of preliminary ozone control measures in phase II, its concentration and associated mortality have continued to rise.[4,5] Previous studies have shown that single-pollutant analysis underestimates cumulative health risks and leads to uneven policy effectiveness (the "whack-a-mole effect"),[6,7] and a recent multi-pollutant ($PM_{2.5}$ and ozone) study overlooked key spatiotemporal population dynamics and short-term exposure risks,[8] while short-term exposure significantly increases the risk of acute diseases.[9–11] However, existing studies on short-term exposure have either not considered provincial-level differences and ozone pollution[12] or have used only single-year data, making them unable to effectively assess the long-term health impacts of policy interventions.[13] Finally, climate risk factors like extreme temperatures directly threaten health[14,15] and also induce pollution-mediated cascading risks by affecting air quality,[16,17] but their cascading health risks have not been fully analyzed. Therefore, this study aims to more effectively assess health inequality by comprehensively analyzing the health risks of $PM_{2.5}$, ozone, and extreme climate, and incorporating spatiotemporal population dynamics.

Despite advancing global air quality improvements and climate governance, regional health risk disparities continue to widen.[18] Previous studies demonstrate that environmental exposure inequality remains pervasive across nations.[19,20] Sub-national-level analyses reveal pronounced regional heterogeneities: Western research tends to prioritize racial exposure disparities,[21] while Chinese studies largely focus on the urban-rural dichotomies.[22–24] A common thread in these studies is their focus on health inequalities arising from different socioeconomic status (SES). Some studies also explore intersecting dimensions such as education level,[25,26] the built environment,[27] and digital finance.[28] Concurrently, disparities in environmental exposure, in turn, shape the long-term migration decisions of the population.[29] However, persistent gaps remain in understanding how exposure inequality translates into health risk disparities—particularly regarding interprovincial variations in health inequality across China. This gap is critical given emerging evidence suggesting that differences in sociodemographic factors, such as (e.g., aging populations, baseline mortality) may have a greater influence on health burdens than differences in exposure levels themselves.[30] China's interprovincial sociodemographic divergence far exceeds its urban-rural disparities, indicating that traditional urban-rural frameworks likely underestimate the extent of regional heterogeneity in shaping health outcome. Admittedly, provincial-level analysis may not fully capture intra-provincial gradient differences (e.g., urban-rural disparities); however, existing research indicates that inter-provincial differences remain the dominant contributor to regional disparities in air pollution exposure in China (compared to urban-rural gaps).[31] For instance, in the average mortality rates for various diseases caused by $PM_{2.5}$ exposure, the urban-rural disparity is approximately 1.6-fold,[22] whereas the difference between provinces can be as high as 3.4-fold (Hainan and Xinjiang).[32] This profound inter-provincial heterogeneity is a primary driver of national-level health inequality and represents a key scale for environmental and health policy interventions within China's governance context.

Current research exhibits two critical limitations. First, the lack of systematic integration of multiple risk factors, as well as the concurrent assessment of multi-pathway exposures, leads to health risk underestimation, and consequently, results in overlooked synergistic policy effects. Second, prevailing health inequity analyses constrained by urban-rural frameworks fail to capture provincial sociodemographic heterogeneity's latent impacts on health risks, making it difficult to explain the vast inter-provincial heterogeneity and its dominant role in shaping national health risk disparities. Based on the shortcomings of prior research, we aim to address two key questions: How do provincial health inequalities, driven by exposure to various risk factors (such as air pollution and climate risks factors), evolve under policy interventions and sociodemographic dynamics? What are the underlying mechanisms driving these health inequalities?

Through an integration of epidemiological modeling with climate, socioeconomic, demographic, and cause-specific mortality datasets, this study aims to offers valuable insights into spatial and temporal disparities of $PM_{2.5}$, ozone, and temperature extremes at the provincial level in China. On this basis, the synergistic mechanisms of health inequalities—such as different driving factors (sociodemographic change) and multiple risk factors (climate-pollution synergies)—were identified and analyzed. Thus, the underlying tension regarding the imbalanced distribution of health benefits under multi-objective environmental policies is revealed.

RESULTS

This study employs a novel analytical framework titled "Multiple factors—Integrated assessment—Synergistic analysis" for the evaluation of health inequalities due to environmental risk factors. This framework has three integral parts (Figure 1) and the framework has three integral parts:

(1) *Multiple risk factors data input.* High-resolution datasets were utilized for key environmental risk factors, including air pollution ($PM_{2.5}$, ozone) and climate extremes (heatwaves, cold spells). For air pollution risk factors, population-weighted exposure levels were calculated by integrating these data with high-resolution population data. For climate risk factors, the number of heatwave and cold spell days was quantified based on extreme temperature thresholds.
(2) *Integrated assessment of health inequality.* Multiple epidemiological models were established for various risk factors, considering both long-term and short-term exposure. These models were designed to quantify the health burdens and economic losses attributable to these multiple risk factors, thereby allowing for an integrated assessment of health inequality.
(3) *Synergistic mechanism Analysis.* To quantify the synergy of various driving factors, the Global Burden of Disease (GBD) factor decomposition method is employed (supplementary information S1). To address the synergy of multiple risk factors, this study first identifies their correlation laws through an analysis of historical evolution characteristics, and then corroborates the underlying mechanisms by referencing established literature in the field.

Further methodological details, including data sources (used to explain data processing methods in detail), parameter settings (used to estimate health burdens and economic losses), the Gini coefficient calculation method (used to measure the level of inequality), are provided in the supplementary information S2–S5.

Integrated assessment of health inequality

This section evaluates health inequities induced by multiple risk factors through dual dimensions: physical metrics (disease burden) and monetary valuation (health economic losses).

Health risks of air pollution

$PM_{2.5}$ short- and long-term exposure. Between 2000 and 2013, $PM_{2.5}$ concentrations across China and its provinces exhibited a fluctuating upward trend. By 2013, 27 provinces exceeded the Grade II National Ambient Air Quality Standard (35 μg/m^3). This corresponds to about 90% of China's provinces suffering from severe fine particulate pollution (Figures 2A and 2B). China's Clean Air Action achieved substantial $PM_{2.5}$ reductions, with the national annual average concentration first falling below the 35 μg/m^3 standard in 2018 (Figure 3A). Notably, the Beijing-Tianjin-Hebei region, Yangtze River Delta, and Pearl River Delta exhibited marked air quality improvements. However, seven provinces (Hebei, Shanxi, Anhui, Shandong, Henan, Xinjiang, and Tianjin) in North and Central China persisted in exceeding the national standard by 2023 (Figure 2C), characterized by higher industrial output shares, elevated population density, and larger vehicle fleets. Compounded by economic

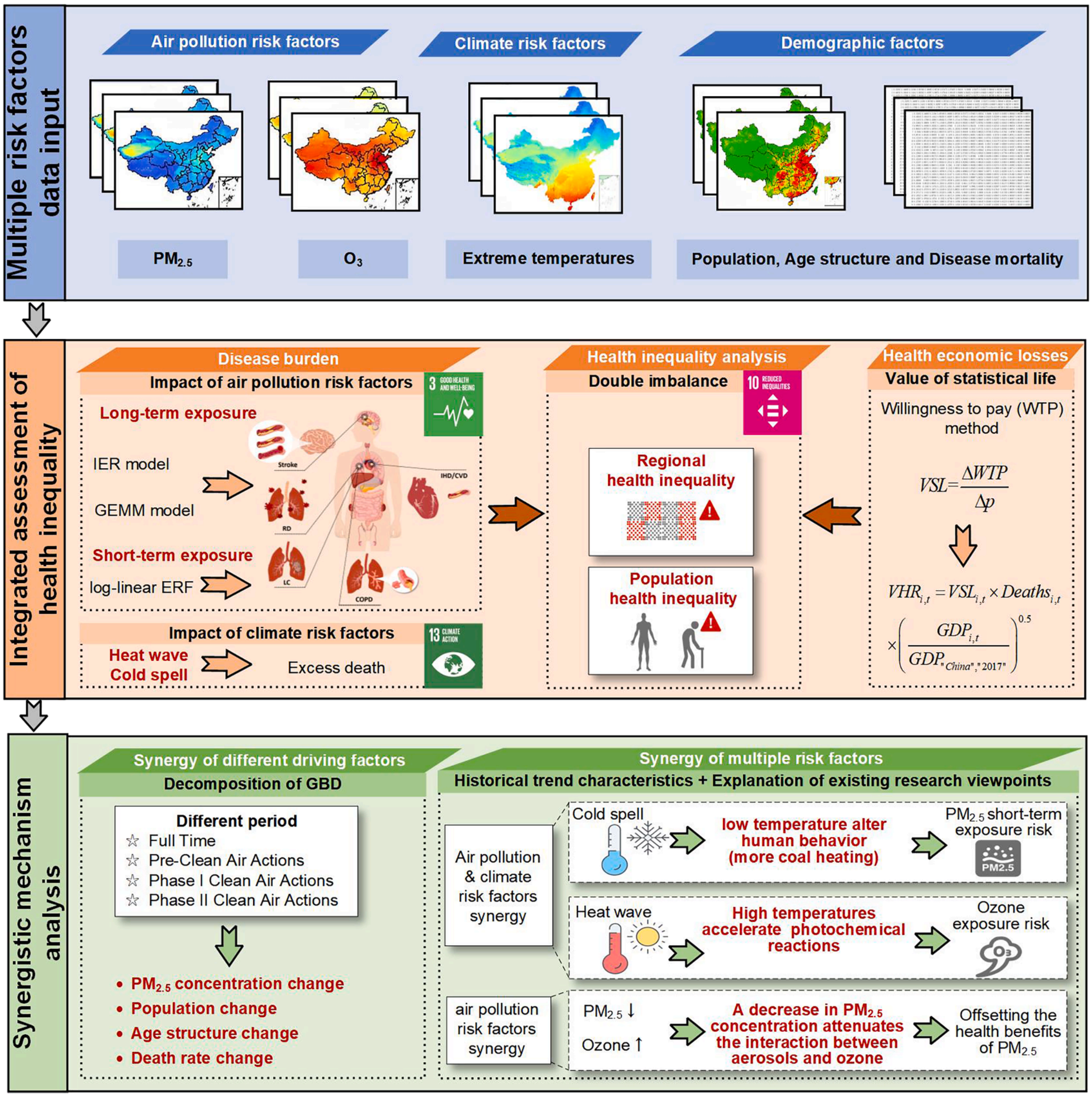

Figure 1. Research framework

development pressures and weaker environmental governance capacity, interprovincial economic disparities have exacerbated regional $PM_{2.5}$ exposure disparities inequality.

Health risks of short-term exposure to $PM_{2.5}$ significantly improved, but inequalities embedded in health benefits. Prior to 2013, short-term $PM_{2.5}$ exposure caused 1041.5 thousand (574.4–1531.8 thousand) premature deaths (Figure 3A), concentrated predominantly in Shandong, Henan, and Hebei provinces. These regions, representing 19.5% of the population, accounted for 40% of total health losses (Figure 2A). Emergency room visits (ERV) attributable to short-term $PM_{2.5}$ exposure surged from 35.3 million (28.9–39.6 million) in 2000 to 226.8 million (192.1–248.5 million) in 2013—a 6.5-fold increase (Figure 3B). China's two-phase Clean Air Action implemented post-2013 achieved significant progress: deaths attributable to $PM_{2.5}$ pollution (DAPP) declined by 94% by 2023 compared to 2013 levels, while $PM_{2.5}$-related ERV decreased by 89% (Figures 2C, 3A, and 3B). Specifically, during phase I (APPCAP), 169.7 thousand (93.8–249.0) premature deaths were averted, benefiting 50.6% of the national population. Phase II (FAP) further prevented 244.3 thousand (134.9–358.8) deaths, extending to 92.7% of population. However, the distribution of health benefits remained highly uneven (Figure 2E). In phase I, about 80% of the gains were clustered among only 13.5% of the population. This disparity reflects a complex interplay of structural factors, including: (1) regions with the most severe baseline pollution, where interventions could yield rapid gains; (2) an administrative focus on officially designated key regions (e.g., the Beijing-Tianjin-Hebei region); and (3) the greater governance capacity of more economically developed provinces. Although the situation improved marginally in phase II, with the beneficiary population expanding to 19.0% as seven provinces experienced

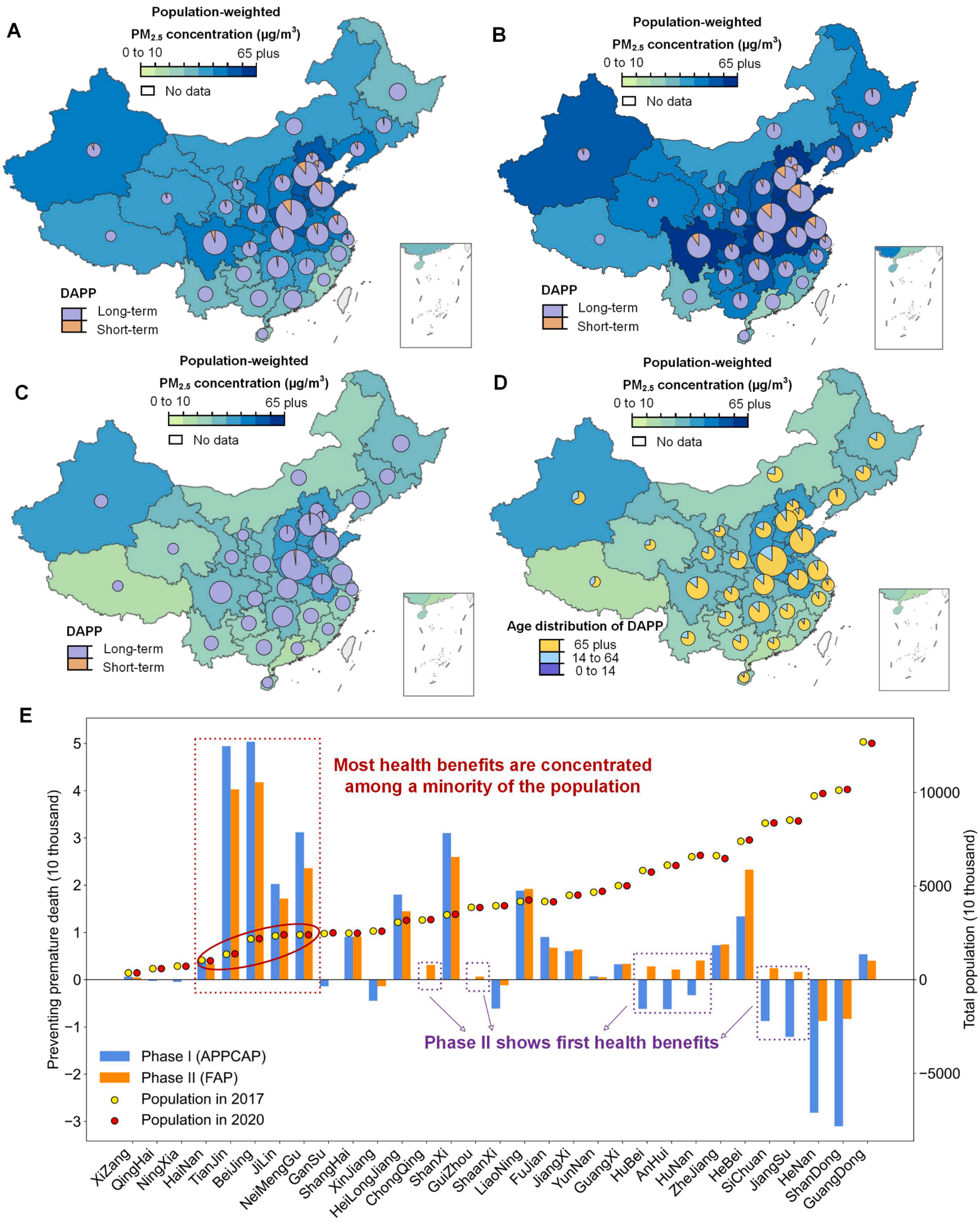

Figure 2. Spatiotemporal dynamics of population-weighted $PM_{2.5}$ concentrations and DAPP

(A) $PM_{2.5}$ concentrations and deaths in 2000.
(B) $PM_{2.5}$ concentrations and deaths in 2013.
(C) $PM_{2.5}$ concentrations and deaths in 2023.
(D) Age distribution of $PM_{2.5}$ deaths in 2023.
(E) Cumulative health benefits and total population. Standard map production based on GS (2019) 756 with no modifications to the base map boundaries.

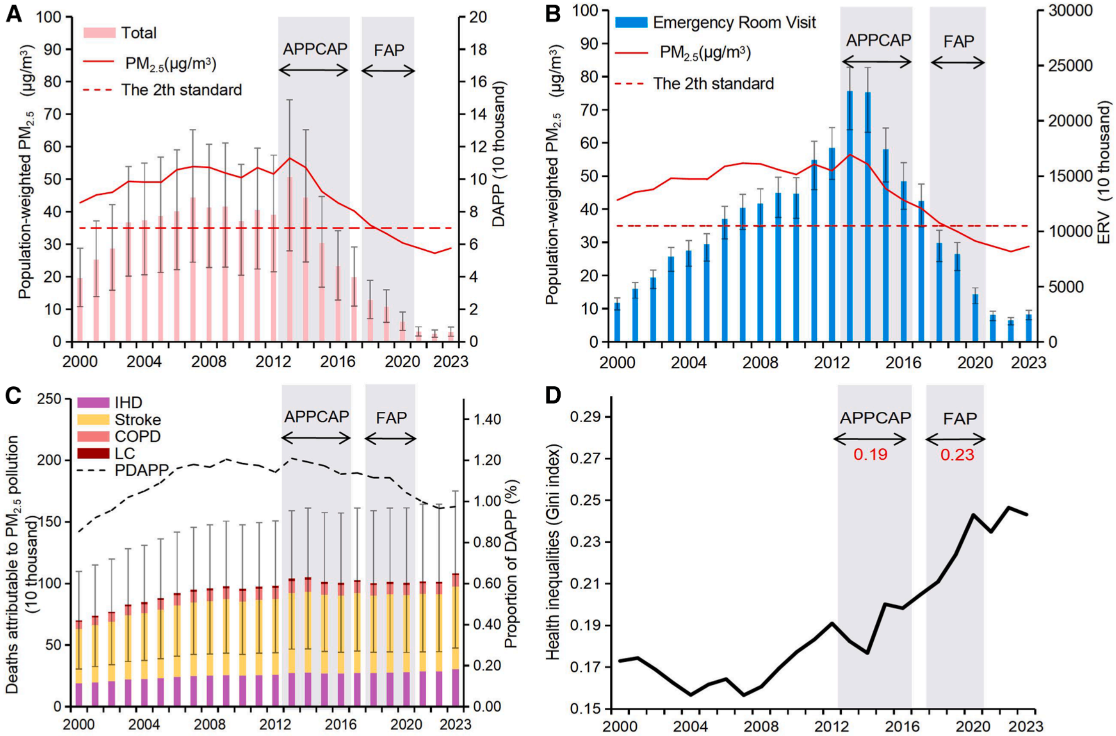

Figure 3. Health risks of short-term exposure and long-term exposure to $PM_{2.5}$

(A) Deaths attributed to short-term exposure to $PM_{2.5}$. The 2th standard is the Grade II National Ambient Air Quality Standard.

(B) ERV attributable to short-term exposure to $PM_{2.5}$. Emergency room visit (ERV).

(C) Deaths attributable to long-term exposure to $PM_{2.5}$. Proportion of total deaths attributed to $PM_{2.5}$ (PDAPP).

(D) Health inequality index of $PM_{2.5}$ pollution. The calculation method of Gini index is shown in supplementary information S4. Error bars refer to the 95% confidence intervals. Phase I focuses on the control of PM_{10} and $PM_{2.5}$, phase II sets emission reduction targets for SO_2, NOx, and VOCs, and phase III has not yet reached its planned deadline, so it is not considered in this study.

benefits for the first time, the distribution of these benefits remained unequal.

The continuous decline in $PM_{2.5}$ concentration has not led to a substantial improvement in the health risks associated with long-term exposure. During phase I (APPCAP), the annual growth rate of DAPP decreased from 3.0% (2.8–3.2) pre-policy to 0.9% (0.6–1.3). However, the overall upward trend in DAPP persisted. In phase II (FAP), strengthened $PM_{2.5}$ controls reduced DAPP by 0.8% (−0.8–0.0), notably curbing rapid deterioration of respiratory diseases (Table S5). However, the policy effects were not sustained, with DAPP rebounding post-2021. By 2023, DAPP increased by 43.3 (35.8–118.1) thousand compared to 2013's peak $PM_{2.5}$ levels (Figure 3C). Eighteen provinces exhibited rising DAPP trends, notably Henan, Shandong, and Liaoning—collectively accounting for 52.2% of national DAPP increments despite comprising only 17.3% of the population. These provinces share high population density and accelerated aging: Henan and Shandong rank second and third nationally in total population, while Liaoning is the highest proportion of residents aged 65 and older in China. These findings suggest partial success of the Clean Air Action, yet underscore the need for enhanced policy implementation.

Overall, the health benefits from the improvement in short-term exposure are not sufficient to offset the increased health risks caused by long-term exposure, and the overall health inequality has not been alleviated (Figure 3D) (To ensure the robustness of the results, we summarized six studies employing the same exposure response function and comparing their estimates of pre-existing deaths attributable to long-term $PM_{2.5}$ exposure, demonstrating that the estimates come from our study fall within a reasonable range [supplementary information S2]). Previous studies have assessed phase I,[2,3] while we further evaluated the benefits of phase II and found that the second-phase policies are still insufficient to reverse the rising trend of $PM_{2.5}$-related risks. Moreover, the inequality within the health risks has worsened, with a small portion of the elderly population (14.9%) shouldering the majority of health losses (81.9%) (Figure 2D). Given China's aging population trend, this situation may become increasingly severe in the future.

Ozone short- and long-term exposure. Rapidly rising ozone concentrations have led to escalating health risks, with short-term exposure risks now surpassing those of $PM_{2.5}$. As shown in Figure 3A, annual mean ozone concentrations remained stable (variation <3 $\mu g/m^3$) during 2000–2016, then surged from 86 $\mu g/m^3$ in 2017 to 103 $\mu g/m^3$ by 2019. This marked the first exceedance of WHO's MDA8-based safety threshold (100 $\mu g/m^3$), with an annual growth rate 6-fold higher than the preceding 17-year average. Benefiting from phase II pollution control

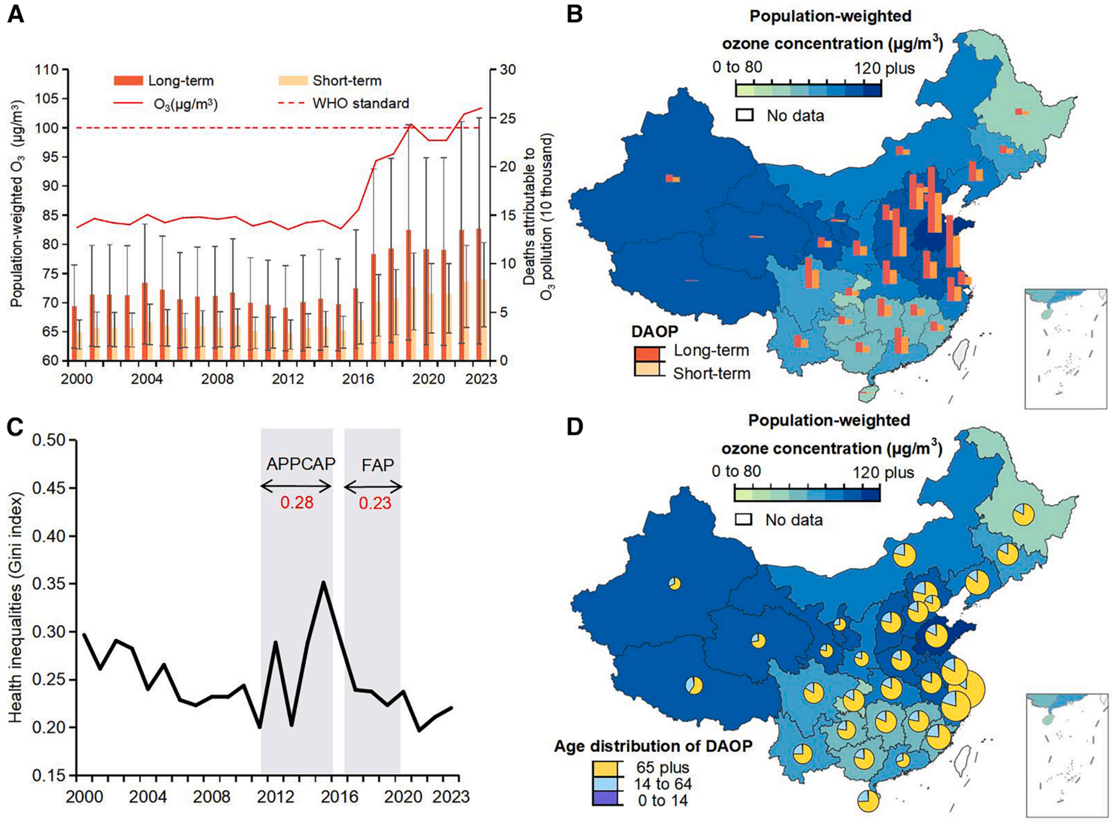

Figure 4. Health risks of short-term and long-term ozone exposure

(A) Time trend: deaths from long-term and short-term ozone exposure.

(B) Spatial distribution: deaths from long-short-term ozone exposure in 2023.

(C) Health inequality index of ozone pollution.

(D) Age distribution of ozone deaths. Error bars refer to the 95% confidence intervals. Standard map production based on GS (2019) 756 with no modifications to the base map boundaries.

policies targeting coordinated NO_x and VOCs precursor reductions, ozone concentration growth rates moderated post-2019. However, exceedances persisted during 2022–2023. In 2023, long- and short-term DAOP reached 136.5 (17.3–250.2) thousand and 83.6 (34.9–121.6) thousand, respectively—a 2-fold and 3-fold increase from 2000 levels. While long-term deaths attributable to ozone pollution (DAOP) remain substantially lower than DAPP, short-term ozone exposure risks now exhibit a surpassing trend. This highlights that the acute health risks associated with ozone pollution warrant greater attention.

The Clean Air Action has mitigated health inequality associated with ozone pollution. Spatially, the highest DAOP occurred in Shandong, Jiangsu, and Henan provinces (Figure 4B), were high population density and intense traffic result in elevated pollution exposure and vehicular emissions. Conversely, Ningxia, Qinghai, and Tibet—despite ozone concentrations exceeding 100 μg/m^3—exhibited lower health burdens due to sparse populations and reduced exposure levels. Unlike $PM_{2.5}$-driven disparities, ozone pollution demonstrates weaker regional health inequality. Specifically, during Phase I when air pollution control focused on $PM_{2.5}$ mitigation, health inequality from ozone pollution remained high (GI = 0.28), peaking in 2015 (GI = 0.35). In phase II, ozone control measures were progressively implemented. Although ozone concentrations continued rising, inequality significantly improved (GI = 0.23) (Figure 4C). However, pronounced health inequality persisted: 78.2% of total health losses were borne by a minority elderly population (14.9%), with this inequality being particularly acute in provinces experiencing accelerated aging (Figure 3D).

Health economic losses due to air pollution. As shown in Figure 5A, air pollution cumulatively caused 59219 billion CNY in economic losses over 24 years—equivalent to half of China's 2023 GDP, with $PM_{2.5}$ and ozone contributing 51475 billion CNY and 7,744 billion CNY, respectively. Long-term $PM_{2.5}$ exposure drove the majority of losses, rising from 672 billion CNY (2000) to 3523 billion CNY (2023). The 2023 $PM_{2.5}$-related losses alone accounted for 2.8% of China's GDP. Although ozone-related economic losses were comparatively lower, they surged 8-fold from 96 billion CNY (2000) to 775 billion CNY (2023). Under persistent ozone concentration increases, ozone-induced health economic burdens are projected to escalate further.

Aging populations and regional development disparities exacerbate interprovincial inequality in health-related economic losses. As shown in Figure 5B, regions with higher economic losses

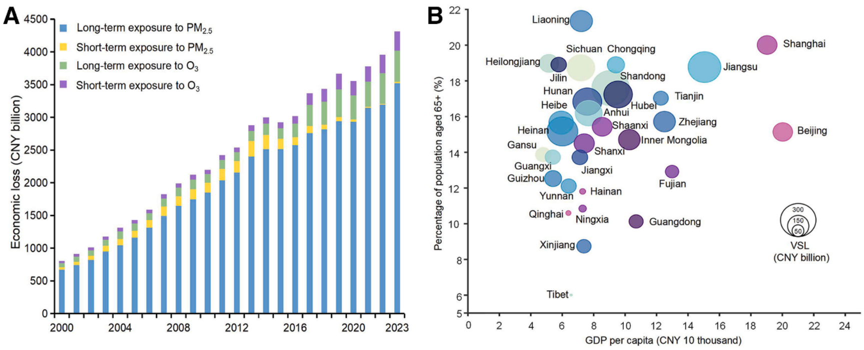

Figure 5. Spatiotemporal characterization of health economic losses

(A) Economic losses from varying levels of air pollution exposure.

(B) Long-term $PM_{2.5}$ exposure economic losses in 2023. The size of the circle represents the absolute value of the change in economic loss.

generally exhibit more pronounced population aging, aligning with existing research.[33] Building on this, we reveal provincial-level spatial heterogeneity in China's health-related economic losses. Based on aging demographics and economic development, provinces cluster into four typologies: high-risk pressure, moderate composite, low-risk potential, and high-risk spillover. (1) High-risk pressure type predominantly characterizes eastern coastal regions (e.g., Shanghai, Beijing, Tianjin, and Jiangsu). These economically advanced, densely populated urban clusters face elevated environmental exposure risks due to accelerated industrialization and urbanization, creating a compounding "economic prosperity-advanced-age vulnerability" effect that amplifies health-related economic losses. (2) Moderate composite type predominantly characterizes central regions (e.g., Shandong, Hubei, and Hunan). As demographic giants in transitional economic and aging stages, these provinces confront dual challenges: uneven distribution of medical resources and progressive population aging. Despite moderate pollutant levels, they experience disproportionate health-related economic losses. (3) Low-risk potential type prevails in western China (e.g., Tibet, Qinghai, and Xinjiang). Characterized by low economic development and aging rates, their health losses primarily stem from inadequate infrastructure and insufficient public health services. However, latent risks escalate with demographic shifts and climate change intensification. (4) High-risk spillover type predominantly occurs in northeastern and northern China (e.g., Liaoning, Hebei). These provinces face dual pressures of challenging economic transitions and accelerated aging. The decline of traditional industries has triggered outmigration of working-age populations, exacerbating health-related economic losses that spill over to adjacent regions and amplify regional health crises.

Health risks of climate change

Health risks from extreme heat events have surpassed historical levels and impacts from cold spells. Under the global warming trend, climate change is intensifying "temperature volatility," leading to frequent extreme temperature events. During 2000–2023, heatwaves and cold spells caused 105.0 thousand and 191.7 thousand excess deaths, with economic losses of 276 billion CNY and 401 billion CNY, respectively. Notably, heatwave-related fatalities in the recent five years (2019–2023) equaled the cumulative total of the preceding two decades and were 1.5 times higher than cold spell impacts. Over the past two years, heatwave-attributable excess deaths and economic losses surged 2.5-fold and 6-fold compared to the previous decade (2022: 30.4 thousand deaths/97 billion CNY; 2023: 12.9 thousand deaths/41 billion CNY) (Figure 6).

Extreme temperatures and socio-demographic characteristics forming a compound amplification effect, causing health inequality to exhibit a "Bipolar" characteristic. On one hand, older adults (aged 65 years and older) face the most pronounced risks, exhibiting 3-fold and 2-fold higher excess mortality rates compared to the 0–14 and 15–64 age groups, respectively. This disparity is closely linked to the high prevalence of underlying diseases among older adults and extreme temperature-triggered cardiovascular/respiratory decompensation mechanisms. Notably, working-age populations (15–64 years) still bear twice the mortality risk of children, primarily driven by systemic exposure to occupational heat stress (e.g., outdoor labor) and cold-related injuries.[34] On the other hand, western China exhibits a phenomenon of "Low mortality count—high mortality rate": despite lower absolute deaths, excess mortality rates associated with extreme temperatures are 30% and 14% higher than those in eastern and central China. This latent inequality in mortality risk has long been overlooked in previous research (Table S6). This can be attributed to the combined effect of two core factors: healthcare accessibility and climate vulnerability. An empirical analysis was conducted to link mortality rates with these two factors (supplementary information S3). First, regarding healthcare resources, western regions significantly lag behind in medical service quality and infrastructure coverage.[35] This disparity implies that residents experiencing illnesses induced by extreme weather are at greater risk of mortality due to delayed and insufficient medical treatment. Second, concerning climate vulnerability, the western regions' inherent socioeconomic and geographical disadvantages—such as slower economic development and limited penetration of adaptive infrastructure (e.g., air conditioning)—increase exposure risks and reduce adaptive capacity.[36] Consequently, populations in these areas tend to suffer more severe health impact when exposed to extreme weather events of comparable intensity.

Synergistic mechanisms analysis

Synergy of different driving factors

Although air pollution and climate change could affect human health, which are not the root cause. From the perspective of social epidemiology's "Fundamental Cause Theory," deep-seated socioeconomic factors are the ultimate drivers of health inequality. Therefore, a decomposition method from GBD study was applied to separate the contributions of three key drivers: population size, age structure, and disease mortality rate.[37] Among these factors, variations in the disease mortality rate are considered to reflect disparities in social medical factors.

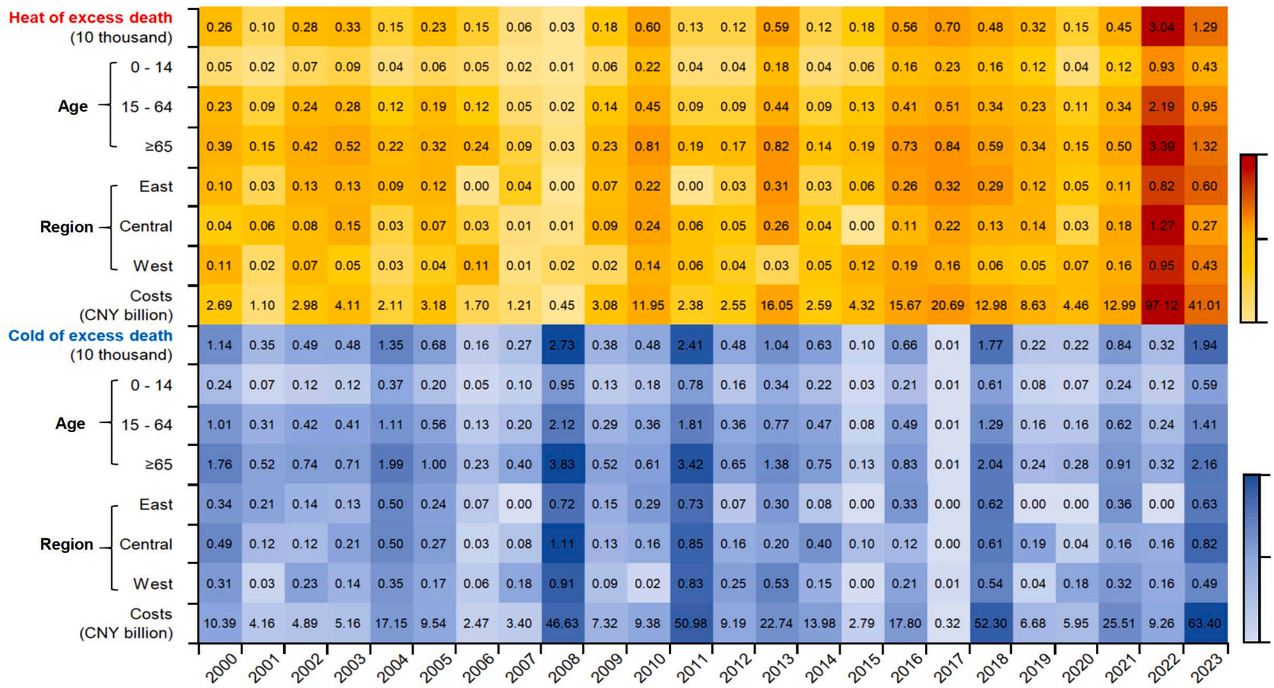

Figure 6. Cold- and heat-related excess deaths and economic loss (2000–2023)

The value of the "Age" element is the standardized mortality rate. The unit is the number of deaths per 100,000 population.

In population size, China's total population exhibited slowing growth followed by decline during 2000–2023, yet remained substantial in scale (Figure 7B). Notably, Henan, Hunan, and Hubei provinces—occupying merely 6% of national territory—reside 16% of China's population,[38] contributing over 50% of DAPP (Figure 2). This concentration creates pronounced "high pollution-high vulnerability" dual pressures in central China (Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, and Chongqing). The demographic-environmental carrying capacity imbalance not only intensifies pollution emission density per unit area but also amplifies $PM_{2.5}$ exposure through high-density settlement patterns, forming regionally clustered environmental health risks. In age structure, from 2000 to 2023, China's elderly population surged by 51.4%, accounting for 14.9% of the total population (Figure 7C). Their proportion of DAPP rose from 71.1% to 84.4% (Figure 2D), highlighting intergenerational health inequities amid rapid aging. Due to declining physiological resilience and cumulative chronic diseases, older adults exhibit heightened vulnerability to $PM_{2.5}$ exposure, resulting in significantly elevated premature mortality rates compared to other age groups.

Geographic disparities in disease mortality further expose structural inequities in healthcare resource allocation. Analysis reveals that while disease risks from long-term $PM_{2.5}$ exposure declined significantly with decreasing $PM_{2.5}$ concentrations (Figure 7A), case fatality rates for four $PM_{2.5}$-related diseases remained markedly lower in eastern China compared to central-western regions (Figure 6D). This spatial gradient implies an uneven distribution of high-quality medical resources across regions. Decomposition analysis indicates that reducing disease mortality in central-western China to eastern benchmarks could theoretically avert 2565.2 (1129.0–3936.2) thousand premature deaths (2000–2020). This numerical gap quantifies the substantial impact of imbalanced healthcare resource allocation on health equity (Figure 8A). Notably, while $PM_{2.5}$ reductions achieved an annual decline of 157.3 (154.7–247.7) thousand in national DAPP (2018–2020). Aging-driven structural pressures intensified, from 2000 to 2020, DAPP increased by 3736.8 (1633.2–5130.7) thousand, with annual growth rising from 241.7 (105.8–350.0) to 345.7 (149.8–468.1) thousand, resulting in partial offsetting of environmental governance gains by accelerated aging (Figure 8B).

Synergy of multiple risk factors

This section analyzes the synergistic effects among multiple risk factors, including the synergy between air pollution and climate risk factors, as well as the synergy among different air pollution risk factors themselves.

Cold spells exacerbate the disease burden attributable to short-term $PM_{2.5}$ exposure. Theoretically, extreme cold increases heating demand—particularly through coal combustion—elevating $PM_{2.5}$ concentrations and subsequent public health impacts. Centralized heating in China's northern regions kicks off in mid-November, and coal consumption due to heating will peak during that time frame. This study analyzed winter heating provinces exclusively, lagging cold spell-attributable excess deaths (CED) by one period and comparing CED trends with annual DAPP variation rates. We revealed synchronized fluctuations between short-term DAPP and CED (Figure 9A), indicating that $PM_{2.5}$ spikes from coal-based heating during extreme cold intensify short-term health risks. Existing studies demonstrate

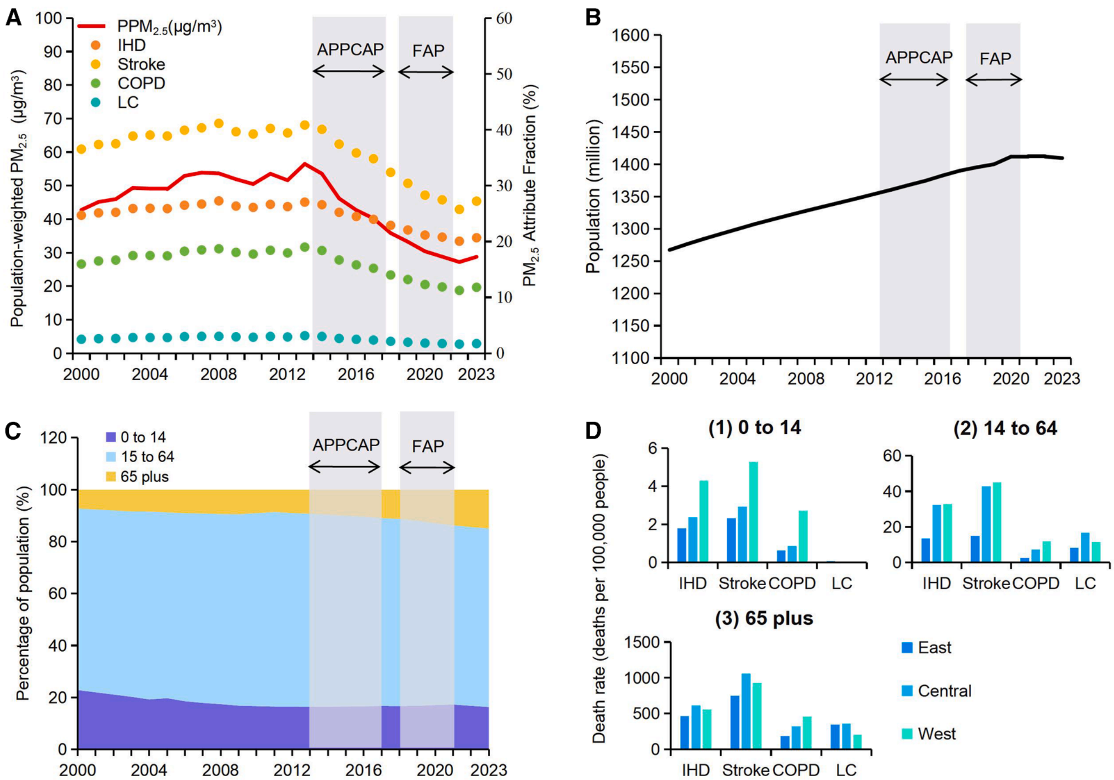

Figure 7. Changing Drivers of DAPP

(A) $PM_{2.5}$ concentration and attribute fraction.

(B) Population size.

(C) Age structure.

(D) Benchmark mortality rates in different regions.

that northern China's free heating policy increased winter $PM_{2.5}$ by 4.6 $\mu g/m^3$ annually, elevating cardiopulmonary mortality and reducing life expectancy by 3.1 years.[39,40] Although China's clean heating policies are progressing, coal-dependent systems exhibit infrastructure inertia and vested interests. Transitioning to clean energy requires substantial investments, with economically disadvantaged regions lagging due to fiscal constraints, perpetuating persistent regional health inequities.

Heat waves exacerbate the disease burden attributable to ozone exposure. Heatwaves are intrinsically linked to

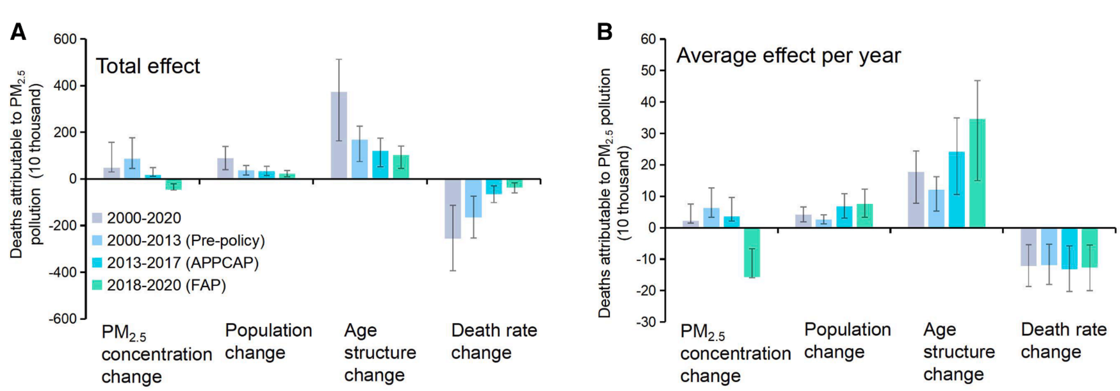

Figure 8. Contribution of different drivers to DAPP

(A) Total effect of different drivers on DAPP.

(B) Average effect of different drivers on DAPP. Error bars refer to the 95% confidence intervals.

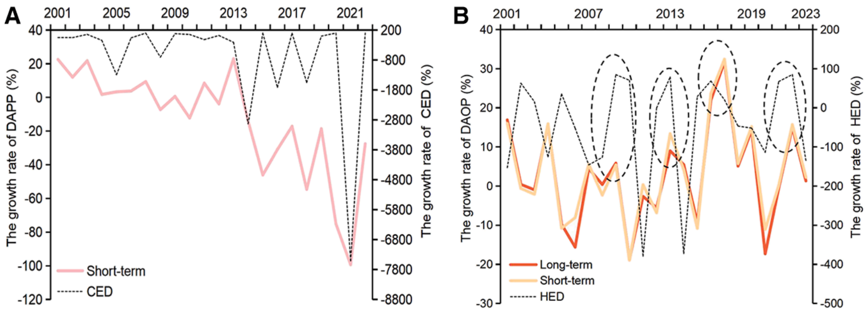

Figure 9. The interactive effects of air pollution and extreme temperatures

(A) $PM_{2.5}$ and cold spell interactions. CED lags one period. The sample is centralized winter heating areas in China, including Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shandong, Henan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

(B) Ozone and heat waves interactions.

ozone formation: when temperatures exceed 28°C, ozone concentrations exhibit significant growth—particularly within 28°C–38°C, where ozone increases linearly at rates up to 4–5 ppb/K.[16] A 21-year observational study further revealed 17.2% higher daily ozone concentrations during heatwaves.[17] Comparing annual variation rates of heatwave-attributable excess deaths (HED) and DAOP from 2000 to 2023, we identified synchronized surges in ozone-related mortality during heatwave episodes (Figure 9B). For instance, during the 2022 extreme heat event, HED increased by 85% and DAOP by 15.7% compared to 2021, reaching historical mortality peaks. These findings indicate that heatwaves during extreme heat episodes stimulate photochemical reactions and ozone formation, thereby exacerbating health risks. As climate change intensifies, global co-occurrences of heatwaves and ozone pollution are projected to surge, worsening exposure inequalities.[41] This synergy will disproportionately escalate health inequalities in climate-sensitive regions and among vulnerable populations.

A substantial 74.9% of the health benefits from $PM_{2.5}$ mitigation were offset by escalating ozone-related health risks. The Clean Air Action averted 700.9 thousand (387.1–1029.3) short-term exposure-related premature deaths from 2013 to 2023 through $PM_{2.5}$ reduction. However, near-surface ozone concentrations surged post-2016 (Figure 4A, supplementary information S5), with ozone pollution causing an additional 553.3 thousand (127.4–934.6) premature deaths from 2017 to 2023 compared to 2016 baselines. This ozone-driven health offset reduced the net health gains to 25.1%. Phase II (2018–2020) mandated a 15% reduction in total NO_x emissions, slowing ozone concentration growth but proving insufficient to counterbalance ozone formation potential driven by rising VOCs emissions and precursor synergies.

This result demonstrates the critical importance of a systematic joint analysis of $PM_{2.5}$ and ozone, as their formation mechanisms, spatiotemporal characteristics, and health pathways have profound intrinsic connections and significant differences. (1) In terms of formation mechanisms, the two share a complex nonlinear chemical relationship. This study found that while $PM_{2.5}$ concentrations dropped significantly, ozone levels paradoxically rose; in this regard, Li et al.[42] used a complex atmospheric chemical transport model (WRF-Chem) to quantify and discover that the decrease in $PM_{2.5}$ during the clean air actions weakened aerosol-ozone interactions, causing changes in meteorological conditions and an increase in photolysis rates, which in turn led to higher ozone concentrations. (2) In terms of spatiotemporal distribution and sources, their characteristics are distinctly different. This study found that $PM_{2.5}$ pollution is more severe in Central and North China, especially during the winter heating season, whereas ozone pollution is more severe in the western regions, particularly in the summer. This difference illustrates that single-pollutant strategies are inadequate, thus necessitating the implementation of coordinated controls across regions and seasons. (3) In terms of health effect pathways, they have different focuses, but their harms are compounded. This study found that $PM_{2.5}$ can penetrate deep into the lungs and enter the bloodstream, with long-term exposure posing greater harm and readily causing chronic damage to the cardiovascular and cerebrovascular systems. In contrast, ozone, as a strong oxidant, poses a greater risk from short-term exposure, easily triggering acute respiratory diseases. Although these two pollutants affect health through different pathways, their combined presence creates a synergistic effect that intensifies the overall damage. Consequently, overreliance on $PM_{2.5}$ controls risks entrenching a "pollution displacement trap", where disadvantaged groups or regions bear disproportionate health burden disparities. The findings of this study provide an important reference for the synergistic control of $PM_{2.5}$ and ozone that the Chinese government is currently advancing: future policymaking must not only jointly control precursors like NO_x and VOCs based on their formation mechanisms but also implement precise, regionalized management according to their different spatiotemporal characteristics and health effects.

DISCUSSION

This study employs a "Multiple factors—Integrated assessment—Synergistic analysis" framework to reveal the effect of health inequality and the underlying mechanisms driven by various risk factors. Our analysis identifies stark regional disparity, with densely populated, aging provinces in the north and central China (e.g., Henan, Shandong) bearing disproportionate health burdens. This is consistent with existing research,[3] but what distinguishes our work is the further revelation of a "hidden health inequality" in China's western regions—where a low "absolute number" of premature deaths masks an extremely high "mortality rate." This finding indicates that beneath the veneer of a sparse population, individuals in the western regions face potentially more severe health risks, and these areas have often been overlooked in previous policy focus. The future allocation of policy resources could move beyond traditional models centered on absolute population or GDP and introduce an indicator system that considers health equity, tilting resources toward high-risk, low-resilience regions, with a focus on strengthening their primary healthcare services and climate change adaptation capacity building.

While existing studies have shown that current clean air action policies have brought significant health benefits, they also indicate that these benefits are still insufficient to offset the exacerbated health risks caused by factors such as population aging.[2,3] We further found an imbalanced distribution of policy benefits and an uneven burden of health losses. The Clean Air Action Plan, despite having widespread coverage, has benefited only 13.5%–19.0% of the population. While older adults make up to only 10% of the total population, they account for over 70% of the health losses associated with air pollution. This unequal demographic distribution signifies an exacerbation of health disparities since aging populations disproportionately carry environmental risk. Furthermore, inter-provincial disparities in health-related economic losses were compounded by aging and uneven regional development trends. The government could establish a refined public health protection system. For example, by linking air pollution and extreme weather early warnings with community-based elderly care systems and chronic disease management apps, it can provide senior citizens with timely, personalized health risk alerts, protective guidance, and emergency shelter support.

Based on the analysis of health inequality, we further systematically identified the pathways that drive this inequality. While clean air actions have significantly reduced the health risks of short-term $PM_{2.5}$ exposure, the concurrent increase in ozone levels has negated 74.9% of these health gains. Meanwhile, even while short-term exposure decreases, long-term $PM_{2.5}$ exposure risks are still on the rise, driven by population aging and interregional development disparities, requiring more comprehensive and longer-term policy measures. In addition, the coupling of extreme temperatures—both heatwaves and cold spells—and air pollution has yielded synergistic health impacts, amplifying existing health inequalities. The synergistic effect elevates the health burden, particularly in vulnerable populations, and necessitates the need for integrated solutions that tackle the combined effects of multiple environmental stressors. In pollution prevention and control, the government could prioritize the synergistic emission reduction of VOCs and NOx to curb the compound pollution of $PM_{2.5}$ and ozone; in urban development, it must coordinate the dual objectives of cooling (e.g., by increasing green spaces) and reducing pollution (e.g., by optimizing layouts).

In summary, this study demonstrates that although environmental policy interventions have effectively reduced exposure risks—realizing an annual reduction of 36.5 thousand DAPP in phase I, to 157.3 thousand DAPP in phase II—they have failed to fully bridge health inequities stemming from regional development disparities and demographic heterogeneity. The compound effects of densely populated central provinces and a rapidly aging population pose unique challenges to China's environmental health governance. China's experience offers critical cautionary insights for global air quality management strategies. It emphasizes the limitations of relying solely on pollutant concentration objectives to limit health risks, especially under the context of rapid demographic transformations. These findings reflect a "dual inequality trap" pervasive in environmental governance across developing economies—where health inequities are compounded by the double effect of unbalanced regional development and population change. This study calls for the core objective of environmental health governance to shift from simply pursuing the reduction of pollutant concentrations to a focus on minimizing health inequality and its associated economic losses. This requires that future policy evaluations (such as the effectiveness assessment of the new round of the "Air Pollution Prevention and Control Action Plan") consider health equity based on demographic structure and regional disparities, helping China and other developing economies worldwide to escape the "double inequality trap."

Amplified by climate change, these compounded inequities represent growing systemic threats to global health and sustainable development. Overcoming this challenge will be critical to the achievement of Sustainable Development Goals (SDG) 3.9 (reducing health impacts from hazardous chemicals and pollution), 10 (reducing inequalities), and 13 (Climate Action). A transition toward multi-factor, equity-oriented governance frameworks is necessary to close the gap between minimizing environmental risks and health equity.

Limitations of the study

This study has several limitations. First, the additional health risk of combined exposure to multiple environmental stressors is not measured. Future studies should establish a compound exposure index system to assess interactive scenarios (e.g., heatwave-ozone and cold spell-$PM_{2.5}$ compound exposures). Second, modification effects of extreme temperatures on air pollution involve complex meteorological and chemical processes. Atmospheric chemistry transport models could assess air quality changes under extreme temperature scenarios. Third, this study disaggregated mortality and age structure data to the provincial level, revealing regional health inequality at the national scale; however, provincial-scale estimates may not capture intra-provincial heterogeneity, especially those between urban and rural areas or among different counties and districts. This may result in either underestimation or overestimation of health risks in densely populated, heavily polluted regions, particularly in provinces with highly uneven pollution distributions. For example, in those provinces with highly concentrated pollution sources and relatively dispersed populations, the provincial average exposure level might underestimate the health risks for residents near highly polluted areas; conversely, it might also overestimate the risks for residents in cleaner areas. Moreover, since the intra-provincial distribution of $PM_{2.5}$ is typically more uneven than that of ozone, it may produce more uncertainties. If the higher-resolution health data such as relative risk of cause-specific mortality become available, a more in-depth and downscaled analysis of typical provinces will be conducted in the future.

RESOURCE AVAILABILITY

Lead contact

Requests for further information and resources should be directed to and will be fulfilled by the lead contact, Li-Jing Liu (liulijing@bit.edu.cn).

Materials availability

The study did not generate new materials.

Data and code availability

Data: All data reported in this paper will be shared by the lead contact upon request.

Code: All custom codes can be available on request from the lead contact. Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

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AUTHOR CONTRIBUTIONS

Conceptualization, L.-J.L. and H.W.; methodology, H.W.; investigation, H.W.; data curation, H.W.; writing—original draft, H.W., and L.-J.L.; writing—review & editing, L.-J.L., H.W., H.-M.D., H.-D.J., P.P., and Q.-M.L.; funding acquisition, L.-J.L., H.-D.J., and Q.-M.L. resources, L.-J.L. supervision, L.-J.L., H.-D.J., and Q.-M.L.

DECLARATION OF INTERESTS

The authors declare no competing interests.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

- KEY RESOURCES TABLE
- METHOD DETAILS
  - Disease burden estimation of air pollution risk factors
  - Disease burden estimation of climate risk factors
  - Monetized estimation of disease burden
- QUANTIFICATION AND STATISTICAL ANALYSIS
  - Estimate the contributions of different driving factors
  - Synergy of climate and air pollution risk factors
  - Uncertainty analysis

SUPPLEMENTAL INFORMATION

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
See supplementary information S9 for all data used in this paper	This paper	N/A
Software and algorithms		
Python	PyCharm Community Edition 2022.1.4	https://www.jetbrains.com/zh-cn/pycharm/
ArcGIS	ArcMap 10.8	https://desktop.arcgis.com/zh-cn/arcmap/index.html
Excel	Microsoft	https://www.microsoft.com/en-ca/microsoft-365/excel
Stata	Stata 17.0	https://www.stata.com/stata17/

METHOD DETAILS

Disease burden estimation of air pollution risk factors

Exposure to air pollution exacerbates disease risks, leading to premature death. The deaths attributable to $PM_{2.5}$ pollution (DAPP) and ozone pollution (DAOP) are calculated as follows:

$$DAPP_{i,t} = \sum_{a,d}\left(PAF_{a,d,i,t} \times Pop_{i,t} \times Rate_{a,d,i,t} \times Age_{a,t}\right) \quad \text{(Equation 1)}$$

$$DOPP_{i,t} = \sum_{a,d}\left(OAF_{a,d,i,t} \times Pop_{i,t} \times Rate_{a,d,i,t} \times Age_{a,t}\right) \quad \text{(Equation 2)}$$

In Equations 1 and 2, $DAPP_{i,t}$/ $DOPP_{i,t}$ is the deaths attributable to $PM_{2.5}$/ozone pollution. $PAF_{a,d,i,t}$/ $OAF_{a,d,i,t}$ is the proportion of deaths attributed to $PM_{2.5}$/ozone pollution caused by disease d in a population with age a at province i in year t; $Pop_{i,t}$ is the population at province i in year t; $Rate_{a,d,i,t}$ is the death rate of disease d for people with age a at province i in year t; $Age_{a,t}$ is the percentage of population with age a to the total population in year t. $PAF_{a,d,i,t}$/ $OAF_{a,d,i,t}$ was calculated $PAF_{a,d,i,t}/OAF_{a,d,i,t} = \frac{RR_{a,d,i,t}-1}{RR_{a,d,i,t}}$, $RR_{a,d,i,t}$ is the relative risk for the population with age a and have the disease d at province i in year t.

Equations 1 and 2 require three datasets: relative risk (RR) values, pollutant exposure levels, and baseline health data. The methodologies for these datasets are as follows:

RR values derive from exposure-response functions (ERFs) quantifying pollutant concentration-health endpoints associations. In air pollution-related health impacts, health endpoints vary depending on exposure duration. Long-term exposure to pollutants can lead to increased risk of chronic diseases causing premature deaths. For chronic health endpoints, $PM_{2.5}$ exposure considers ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD), and lung cancer (LC); ozone exposure involves cardiovascular disease (CVD) and respiratory disease (RD). Short-term exposures result in more complex risk of acute diseases. For acute health endpoints, both $PM_{2.5}$ and ozone exposure were considered solely for all-cause mortality risk, with additional consideration of $PM_{2.5}$-associated emergency room visits (ERV). Following Burnett et al.,[43] RR associated with long-term $PM_{2.5}$ exposure was estimated using the Integrated Exposure-Response (IER) model. The IER model has been widely adopted in health risk assessments of air pollutants due to its structural universality and better alignment with China's context. Although the GEMM model, developed by the same research team, incorporates updated data, this study retained the IER model as the primary risk quantification basis[2,44] to ensure comparability with existing research outcomes. The GEMM model was additionally employed in uncertainty analyses for supplementary evaluation.

$$RR_{a,d,i,t} = \begin{cases} 1+\alpha_{a,d}\left(1 - e^{-\gamma_{a,d}\left(C_{i,t}-C_{0_{a,d}}\right)^{\delta_{a,d}}}\right), & C_{i,t} > C_{0_{a,d}} \\ 1, & C_{i,t} \le C_{0_{a,d}} \end{cases} \quad \text{(Equation 3)}$$

For short-term $PM_{2.5}$ and long-/short-term ozone exposures, this study employed log-linear exposure-response functions following the GBD 2017 methodology (Equation 4). The calculation formula is as follows:

$$RR_{a,d,i,t} = e^{\beta_{a,d}(C-C_0)} \quad \text{(Equation 4)}$$

In Equations 3 and 4, $C_{i,t}$ is the $PM_{2.5}$ concentration at province i in year t; $\alpha_{a,d}$, $\gamma_{a,d}$, $\delta_{a,d}$, $\beta_{a,d}$ and $C_{0_{a,d}}$ are the parameters of ERFs (supplementary information S6).

Pollutant exposure levels were assessed using the latest $PM_{2.5}$ and ozone concentration data (spatial resolution: 1 km, units: μg/m^3) from the China High Air Pollutants (CHAP) dataset. Ozone levels were based on the Maximum Daily 8–Hour Average (MDA8) metric.[45–47] However, CHAP data do not account for population exposure heterogeneity. We further calculated the population weighted $PM_{2.5}$/ozone concentration for each province.

Baseline health data encompass demographic statistics, disease-specific mortality rates, and hospital visitation data. Previous studies often assume nationally homogeneous or temporally static disease mortality and age structures.[2,8,48] This study advances these approaches by: (1) Differentiating disease categories, we integrated region-specific and age-stratified mortality data from the China Cause of Death Surveillance Dataset with age-specific attributable mortality proportion data from the Global Burden of Disease (GBD) database, thereby developing provincial age-specific baseline mortality rates across multiple years; (2) differentiating time-varying provincial age structures using national population census data.

Disease burden estimation of climate risk factors

Climate risk factors primarily focus on extreme temperature events, including heatwaves (extreme high temperatures) and cold spells (extreme low temperatures). These events elevate relative risks of cardiovascular, cerebrovascular, and respiratory diseases, resulting in temperature-attributable excess death (ED). Provincial-level excess death from extreme temperatures was calculated as follows:

$$ED_{i,t} = N_{i,t} \times ER \times D_{i,t} \qquad \text{(Equation 5)}$$

In Equation 5, ED_i is the excess deaths attributable to extreme temperature events at province i in year t; N_i is the average daily non-accidental deaths at province i in year t; ER is the excess risk[15]; $D_{i,t}$ are days of extreme temperature events in year t. Threshold definitions for extreme temperatures referenced established criteria from prior studies (Extreme heat events: Daily Tmax >99th percentile for ≥2 consecutive days; Extreme cold events: Daily Tmin <5th percentile for ≥7 consecutive days.).[15]

Monetized estimation of disease burden

To measure the health economic loss due to premature death, it is necessary to convert the physical quantities of various health endpoints into monetary terms. Referring to West et al.,[49] the value of statistical life (VSL) is first calculated using willingness to pay (WTP) and the unit risk probability (p), and then VSL is used to quantify the monetary value of each health endpoint (supplementary information S7). The calculation formula is as follows:

$$VSL = \frac{\Delta WTP}{\Delta p} \qquad \text{(Equation 6)}$$

$$VHR_{i,t} = VSL_{i,t} \times Deaths_{i,t} \times \left(\frac{GDP_{i,t}}{GDP_{''China'',''2017''}}\right)^{0.5} \qquad \text{(Equation 7)}$$

In Equations 6 and 7, WTP is the amount of money that residents are willing to pay to avoid a unit of death risk; p is the unit risk probability. $VHR_{i,t}$ is the monetized value of health risks at province i in year t; $VSL_{i,t}$ is the residents' extra costs to avoid health risks at province i in year t, and adjusted by the GDP of province i in year t, the elasticity coefficient is set to 0.5[50]; $Deaths_{i,t}$ is the premature deaths attributed to different events at province i in year t.

QUANTIFICATION AND STATISTICAL ANALYSIS

Estimate the contributions of different driving factors

Based on adjustments to the formula for estimating the disease burden of air pollution risk factors, we estimated the contributions of changes in $PM_{2.5}$ concentration, population size, age structure, and mortality rate. Specifically, these were adjusted using the following four methods: (1) $PM_{2.5}$ concentration was fixed to 2013 values; (2) The population size was set to the value in the base year 2000; (3) The age structure was set to the value of the base year 2000; (4) The benchmark mortality rate was set to the value for the eastern region.

Synergy of climate and air pollution risk factors

Cold spells and $PM_{2.5}$: Considering that centralized heating in northern China begins in mid-November, when coal consumption for heating peaks, we lagged cold spell-attributable excess deaths (CED) by one period and compared their trend with the annual variation rate of the disease burden attributable to short-term PM2.5 exposure (DAPP) to determine if a common trend exists.

Heat waves and ozone: We conducted a comparative analysis of the annual variation rates of heatwave-attributable excess deaths (HED) and the disease burden attributable to ozone exposure (DAOP) from 2000 to 2023 to determine if a common trend exists.

Uncertainty analysis

To address inherent uncertainties in epidemiological models and unforeseen exogenous shocks, this study conducted a tripartite uncertainty analysis: parameter uncertainty, model discrepancy, and public health emergencies, thereby ensuring the robustness of health impact assessments (supplementary information S8).

(1) Uncertainty in epidemiological models primarily stems from ERF estimation. For varying exposure durations, we employed the GBD study's IER model and log-linear ERF to calculate health risks. Plausible health risk ranges were derived using the upper (95^{th}) and lower (5^{th}) bounds of parameter estimates from both models. Furthermore, unlike prior studies,[2] we incorporated province-specific age structures and mortality rates, enabling more precise quantification of aging impacts. This granular approach elucidates why long-term exposure-associated DAPP remains unmitigated despite policy interventions. Age-related vulnerability was captured using age-specific baseline mortality rates. Therefore, the uncertainty of the age-stratified RR values was not further explored. Additionally, we have defined new extreme temperature thresholds and re-estimated the excess mortality attributable to climate change. The magnitude of change in the results under the new threshold definitions is approximately 5%, which remains robust.

(2) Considering the model discrepancy, we conducted cross-validation using the GEMM. Although GEMM yielded higher estimates for long-term exposure-associated DAPP compared to the IER model, a pattern consistent with prior findings,[51] both models demonstrated concordant change trends, preserving the validity of our core conclusions.

(3) In 2020, China intensified public health interventions in one-third of cities to mitigate COVID-19 transmission risks, implementing phased social activity restrictions. Lockdown measures (January–April 2020) reduced annual $PM_{2.5}$ levels by 1.5 μg/m^3,[52] potentially overestimating Phase II policy impacts. We recalculated $PM_{2.5}$ concentrations excluding COVID-19 effects show Phase II averted 437.4 thousand premature deaths (vs. 471.8 thousand without COVID-19 adjustment), yielding an annualized reduction of 145.8 thousand deaths (vs. 157.3 thousand). These results confirm Phase II's significant health benefits and the robustness of our conclusions.

Although the aforementioned analysis corrected the direct impacts of the COVID-19 pandemic on $PM_{2.5}$ concentrations, other confounding factors including healthcare accessibility, pollution exposure and baseline mortality rates arising from the pandemic disruptions between 2020 and 2023 have not been fully encompassed due to data availability. However, these factors could introduce potential biases into the health benefit assessment from multiple aspects: for example, limitations in healthcare services caused by the pandemic may imply the conservative assessment of the policy's benefits. At the same time, changes in residents' spatiotemporal activity patterns (such as working from home) could underestimate individuals' actual pollution exposure levels. For the baseline mortality rate, considering the underlying data are systematically compiled by the National Bureau of Statistics from various sources, including household registrations, death reports from medical facilities, and population censuses or surveys, it may already incorporate the mortality impact of the COVID-19 pandemic. In summary, despite the underestimations mentioned above, there are still positive health benefits in Phase II. The further discussions are shown in supplementary information S8.