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Who pollutes and who suffers from air pollution in India

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Abstract

Airborne fine particulate matter ($PM_{2.5}$) is the most important environmental risk factor for premature mortality worldwide, and the likely cause of several hundred thousand premature deaths every year in India. Indian households also contribute to ambient $PM_{2.5}$ to different extents from a number of sources, including biomass-burning cook stoves, transport and industrial manufacturing triggered by household consumption. In this study, we quantify the $PM_{2.5}$ contributions by source from, as well as the mortality burden suffered by, individual urban and rural income deciles. We find that the impacts are distributed differently from contributions. Indirect emissions associated with household consumption contribute almost twice as much to ambient $PM_{2.5}$ concentrations as direct emissions from biomass cook stoves. We show that the mortality risk from these indirect sources fall disproportionately on lower-income households, exacerbating the mortality risks they already face from using biomass-burning cook stoves. As a result, economy-wide end-of-pipe controls can reduce inequity in contributions to ambient air pollution. However, due to the overwhelming role of household indoor air pollution in premature deaths among the low-income population, clean cook stoves reduce overall inequality in terms of mortality risks to a far greater extent.

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Introduction

Air pollution is not only among the leading causes of premature mortality worldwide, but possibly a marker of the unequal environmental impacts of economic development. Research shows that higher economic inequality is correlated to higher environmental degradation, particularly in cities and particularly for short-term air and water pollution^{1,2}. A global review shows that lower socioeconomic regions of countries, particularly in North America, UK, Asia and Africa, have higher concentrations of particulate matter (PM)³. Tessum et al.⁴ calculate such pollution equities for racial groups across the US and find that Blacks and Hispanics bear a disproportionately high pollution burden.

This unequal exposure likely exacerbates health inequality. In a cross-country study, PM₁₀ and SO₂ emissions were found to partly statistically explain differences in infant mortality between and within countries⁵. A study of India finds mortality, in general, to be inversely correlated to income and assets⁶. A global study across 29 countries finds cardiovascular disease (CVD) risks to be more closely associated with education- rather than income-inequality⁷. In China, income- and health-inequality were found to strongly correlate, and were mediated by pollution⁸. Adverse health outcomes result not only from exposure, but also people's vulnerabilities to health risks. Here too, there is evidence that vulnerability also increases at lower incomes, due to poorer nutrition, adaptive ability and other immune deficiencies^{9,10}.

What is less clear, though, is how households' contribution to ambient air pollution (AAP) compare to the mortality risks they face from PM_{2.5} concentrations. In India, poor, rural households face mortality risks mostly from the household air pollution (HAP) caused by their own use of biomass-burning cook stoves. However, these stoves also contribute to AAP¹¹. At the same time, higher income, predominantly urban, households contribute to AAP indirectly, from vehicles and the manufacturing of products they consume. Both direct and indirect contributions to AAP present a public health risk to all households, but their relative contribution from households with different consumption patterns is not known.

Our objective in this paper is to bring these aspects together and quantify the net PM_{2.5} pollution inequity in India. We define a new 'pollution inequity index' (PII) that measures the mortality impact per unit of air pollution contributed by households at different income levels. Our study contains three other novelties in methodology compared to previous studies: we present a breakdown of indirect PM contributions by consumption category for different income deciles; we account for different vulnerabilities of income groups in our mortality estimates; and we compare the effectiveness and distributional impacts of stylized pollution mitigation policies that either mitigate cook stoves' PM_{2.5}

contribution with clean cook stoves (“CC” scenario) or install maximum feasible controls on all other (i.e. industry, including agriculture and power, and transport) emission sources (“MCO” scenario).

We know of only two studies that estimate pollution inequities across income classes for PM_{2.5} in terms of premature deaths and account for all PM sources. Zhao et al.¹² show that household direct and indirect emissions contribute roughly equal shares to PM_{2.5}-related mortality in China, and that higher income groups contribute to premature deaths in proportion to their consumption. Chafe et al. find that in India household cooking contributed 26 percent of AAP in 2010.¹¹ However, this latter study does not consider the heterogeneity in PM contributions or impacts across the population. Neither study incorporates differences in households’ vulnerability to air pollution in their mortality estimates.

In order to calculate the relative contributions of direct and indirect emissions for different income deciles, we use a combination of methods for different sources. Broadly, for direct emissions we use technology-specific emission factors of fuels from the GAINS integrated assessment model^{13,14}, including the fuel mix of electricity production, combined with estimates of households’ direct fuel use for heat and electric appliances. For transport, we attribute total passenger transport fuel use to households in proportion to their travel demand by mode. For indirect emissions, industry-specific production based direct PM contributions are calculated in the GAINS model, and to allocate them to households we use a standard household footprinting method that links household consumption expenditure with a multi-regional input-output (MRIO) database and a PM contribution satellite which we derive from the MRIO model’s energy satellite. For completeness, we also calculate non-household emissions from economic activities (e.g. government) and from transboundary and natural sources such as dust. Atmospheric source-receptor relationships contained in the GAINS model are used to derive resulting contributions to PM_{2.5} concentrations. Due to data limitations, we use consumption expenditure as a proxy for income (See SI).

Our study finds that, in aggregate, indirect emissions associated with household consumption contributed almost twice as much to ambient PM_{2.5} concentrations as direct emissions from biomass cook stoves. Furthermore, the mortality risk from these indirect sources fall disproportionately on lower-income households, exacerbating the mortality risks they already face from using biomass-burning cook stoves. As a result, economy-wide end-of-pipe controls can reduce pollution inequity. However, due to the overwhelming contribution of HAP to premature deaths, clean cook stoves reduce overall mortality risks to a far greater extent, and in particular the burden to the low-income population.

Results

We first analyze the distribution of contributions to ambient PM_{2.5} in India in the base year 2010 across income deciles. National annual average ambient PM_{2.5} concentration in 2010 reached approximately 43 µg/m³, of which about 23 µg/m³ can be attributed to Indian household activities (cf Figure 1) through either direct combustion in the household or consumption of goods. The rest includes the contribution from transboundary (i.e. from outside India) and non-anthropogenic sources (black in Figure 1), as well as economic activities outside the household, such as governmental and non-profit institutions, gross fixed capital formation (GFCF), inventory changes, and exports (shaded in grey in Figure 1). We do not attempt to attribute pollution from these activities to households, as neither the data nor conceptual clarity on their links to households are available in the literature.^{15–17}

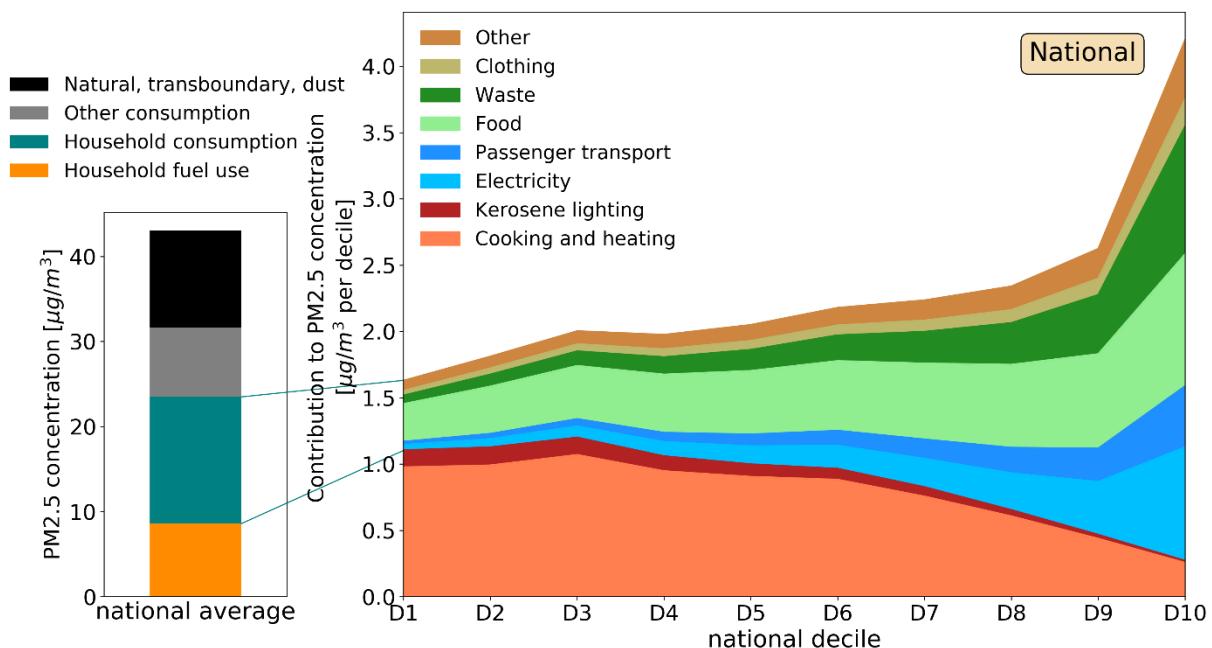


Figure 1 Contribution of consumption patterns to ambient concentration of PM_{2.5} in 2010. The left panel shows total national PM_{2.5} concentration by broad source categories. The two blocks at the bottom amounting to around 23 µg/m³ are driven by households (orange and dark green: direct contribution from household fuel use and indirect contribution through consumption of goods and services) and are the subject of our analysis. The areas on the right panel break down these two contributing parts into household activities over income deciles. The thin green lines between the two panels indicate which types of activities are classified as ‘indirect’.

We break down household activities into several categories in the right panel of Figure 1. At the bottom, ‘Cooking and heating’ and ‘Kerosene lighting’ activities involve direct combustion domestically, contributing about 9 µg/m³ to the ambient PM_{2.5} concentration (or 20 percent of the total). The upper areas of the right panel (blue, green, brownish) represent indirect contributions

along the supply chains of household goods and services as well as waste disposal. The latter includes both open burning of waste, as well as waste collection, recycling and incineration. ‘Passenger transport’ includes both private vehicles and public transportation. These indirect contributions amount to about $14 \mu\text{g}/\text{m}^3$ (33 percent).

The proportion of direct and indirect emissions differs markedly across income groups. Direct contributions are larger in lower income deciles due to heavier reliance on solid fuels and much smaller in higher deciles thanks to better access to cleaner fuels. Indirect contributions, driven by higher consumption of commodities and services, increase sharply and offset the decrease in direct pollution from the fifth decile onward. Indirect contributions from more essential commodities like food and clothing are distributed relatively evenly across deciles, while those from electricity, transportation, and waste are highly correlated to income. In total, therefore, contributions from the highest income decile are more than a factor two higher than those from the lowest decile.

It is noteworthy that food production and preparation, plus waste, together contribute 70 percent or more across deciles, with waste increasing and cooking-related contributions decreasing with rising income. It is also perhaps surprising, considering the public image of Indian cities teeming with traffic congestion, that the share of passenger transport is only 6 percent on average, and only 11 percent for even the highest decile.

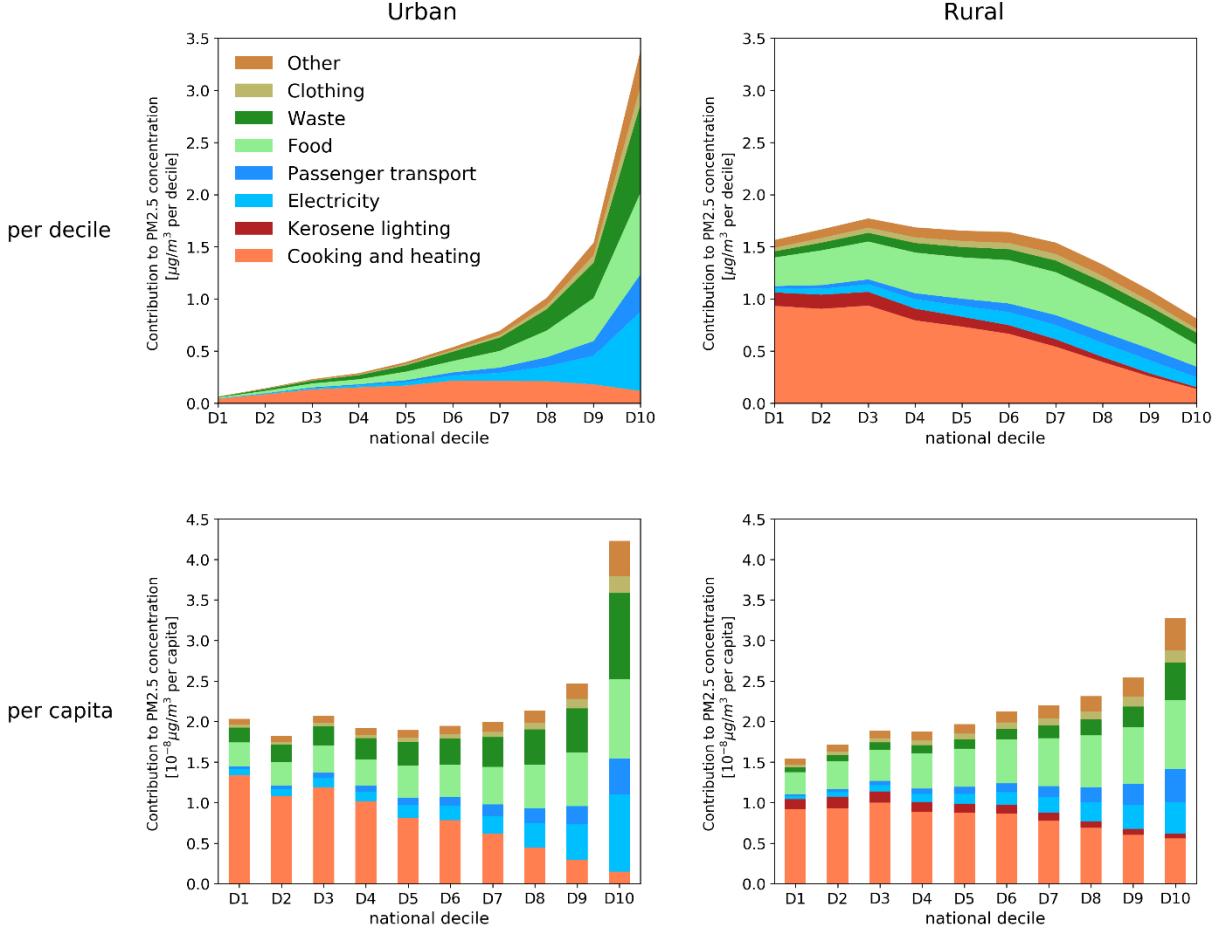


Figure 2 Contribution to ambient PM_{2.5} concentration in 2010 split into urban (left) and rural (right) population. The upper panels show the absolute contribution of urban and rural residents within each national income decile, the lower panels show the per capita contribution. The upper distributions differ because the share of urban vs rural population varies across deciles.

We present contribution patterns of urban and rural population separately in Figure 2, because we expect salient lifestyle differences between the two. The upper panel shows that, in aggregate, the sharp increase in contributions seen in Figure 1 in upper deciles is driven by urban consumption, while the lower deciles are dominated by the rural population. This is largely driven by different shares of urban and rural population in each national decile. On a per-capita basis as well, one can see that in both urban and rural populations decreasing contributions from household solid fuel burning are offset by indirect contributions from consumption activities. However, there are some notable differences.

While the per-capita contribution increases with income almost monotonically in rural areas, the urban population exhibits a plateau at low/middle deciles, but then shows a more than 60 percent increase from the ninth to tenth decile. We find the difference is mainly due to a much faster rate of adoption of clean cook stoves with increasing income among the urban middle class that is offset almost equally by their income elasticities of electricity use and waste generation. In rural households,

solid fuel burning continues even among higher income groups, as contributions from other consumption also increases with disposable income. Other key differences include that rural food PM footprints are higher than urban ones, possibly due to the higher share of grains in their diet, which tend to have higher fertilizer use¹⁸. However, the contribution from waste is much higher for urban households in all deciles, which reflects their relatively affluent lifestyles.

With regards to mortality, in absolute terms, we estimate that 1.19 (1.13-1.25) million deaths in 2010 were attributable to the combination of HAP and AAP. When comparing these household deciles' mortality risks from PM_{2.5} concentrations to their contributions, the pollution inequity becomes starkly evident (Figure 3, left panel). The death rate from PM_{2.5} pollution (dashed lines) decreases with increasing income, while per-capita contributions to pollution (full lines) increase. Similar shapes of this relationship are found for urban and rural population. The resulting Lorenz curves (Figure 3, right panel) show the cumulative population shares associated with total premature deaths, total PM contribution, and total consumption expenditure. These indicate that the inequality in mortality risks far exceeds that of PM_{2.5} contributions but is far less than income inequality (as indicated by the area between the Lorenz and the 45 degree red line).

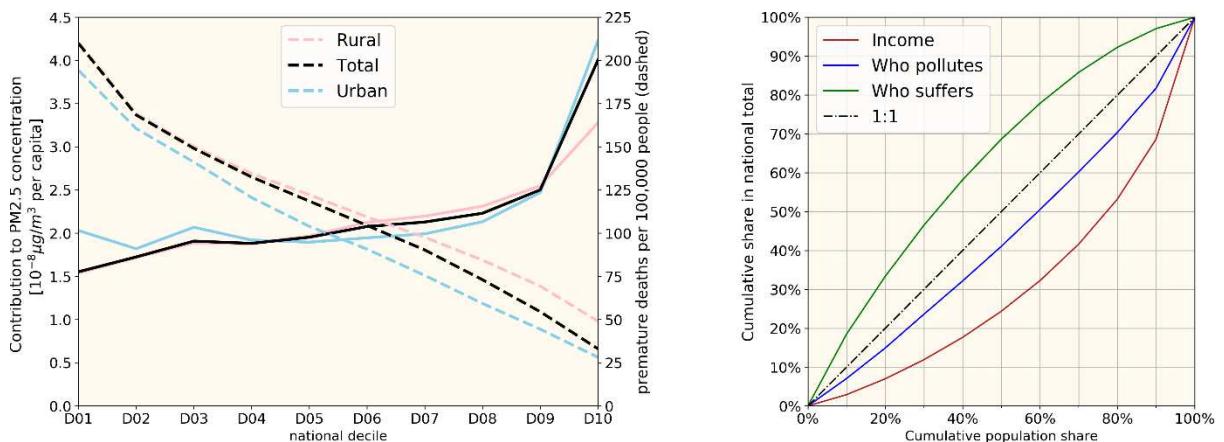


Figure 3 Left panel: Who pollutes (full lines, left axis) and who suffers (dashed lines, right axis) by income decile. The mortality rates, which reflect the income-dependent vulnerability, include effects from ambient as well as from household pollution. Both indicator trends are per-capita. *Right panel:* Lorenz curve (cumulative population share) of consumption expenditure ("income"), PM_{2.5} contribution ("Who pollutes") and premature deaths ("who suffers").

We combine contributions to ambient PM_{2.5} and mortality risk to define the pollution inequality index (PII) — the number of air pollution related premature deaths per unit contribution to PM_{2.5} concentrations. We calculate the PII first using total premature deaths, and then only with respect to AAP. The PII reveals the extent to which households of different income levels suffer pollution-related mortality in excess of their contribution compared to the median household. At the national level, the

median PII for total air pollution-related deaths is 55.5 (mean: 51.6) attributable deaths per $10^{-3} \mu\text{g}/\text{m}^3$ of ambient concentration contributed, while for the poorest and richest deciles the values are 135.2 and 8.3, respectively. Thus, the poorest decile suffers 2.4 times as many deaths per unit of contributed ambient pollution as the national median, while the richest decile suffers 6.7 times fewer deaths per unit of contributed pollution. In other words, the poorest decile is disadvantaged relative to the richest decile by a factor of more than 16. The resulting factor of ‘disadvantage’ when considering only AAP-related mortality, which implicitly focuses only on the distributional impacts of households on each other, is still 8.7 [see SI]. We focus on this AAP-related index PII_{AAP} to assess pollution inequity henceforth.

To understand how different pollution mitigation policies can reduce mortality and these observed inequalities, we examined two policy scenarios, each imposing controls on different PM sources (see SI for details): Clean Cookstoves (CC) and Maximum Controls on Other sources (MCO). Implicitly, the results of each scenario reveal the mortality risk associated with the other, uncontrolled, set of sources. From this, one can ascertain the relative efficacy of the two approaches in reducing AAP, and the extent to which each set of sources contributes to pollution inequity, or the PII.

Figure 4 presents results of these scenarios on the health burden and contribution to ambient $\text{PM}_{2.5}$ concentrations for each decile. Overall, the MCO scenario reduces, *ceteris paribus*, ambient $\text{PM}_{2.5}$ concentrations by $13.8 \mu\text{g}/\text{m}^3$ (32 percent) and AAP related deaths by roughly 80,000 cases compared to our reference case (Figure 4b). However, since HAP remains, total mortality from both factors is reduced by only 7% (Figure 4a). The CC scenario reduces, *ceteris paribus*, ambient $\text{PM}_{2.5}$ concentrations by $8.5 \mu\text{g}/\text{m}^3$ (20 percent) and virtually eliminates HAP, where concentrations are much higher, thereby reducing 690,000 (58 percent) of total premature deaths. Due to the higher use of these cook stoves among the poor, we find that implementing CC reduces mortality among the poorest decile by fifteen times the reduction for the richest decile.

When we consider the impact of these policies on just AAP, the avoided mortality for the MCO scenario exceeds that of the CC in absolute terms for *all* deciles (Fig 4b). That is, lower income households suffer mortality risks from PM contributions of other income groups to a greater extent than from their own cook stoves’ contribution to AAP (Fig 4c). Poorer people have a higher exposure to AAP for a number of reasons related to the distribution of emission sources and population across states, and differences in climatic conditions. For instance, northern states like Bihar have high densities of poor, mostly rural, populations, high shares of solid fuels being used for cooking, as well

as intensive agriculture and other emission sources such as coal power plants. Furthermore, the northern states have a higher prevalence of temperature inversions that lead to higher concentrations for similar levels of PM_{2.5} emissions¹⁹. Consistent with that result, implementing MCO is more effective in reducing the inter-decile inequality in PM_{2.5} contributions to AAP.

The combination of these impacts, as seen in the resulting PII from the policies (Fig 4d), reveals that all households face mortality risks from solid fuel cookstoves roughly in proportion to their contributions (shown in the MCO scenario). On the other hand, when solid fuel emissions are removed (in the CC scenario), the stark inequality in the burden of indirect sources on lower income households is revealed. The difference in the AAP PII between the highest and lowest income decile increases from a factor of 9 to 21 from the reference case to the CC scenario. Lower income households bear a disproportionate burden of total air pollution.

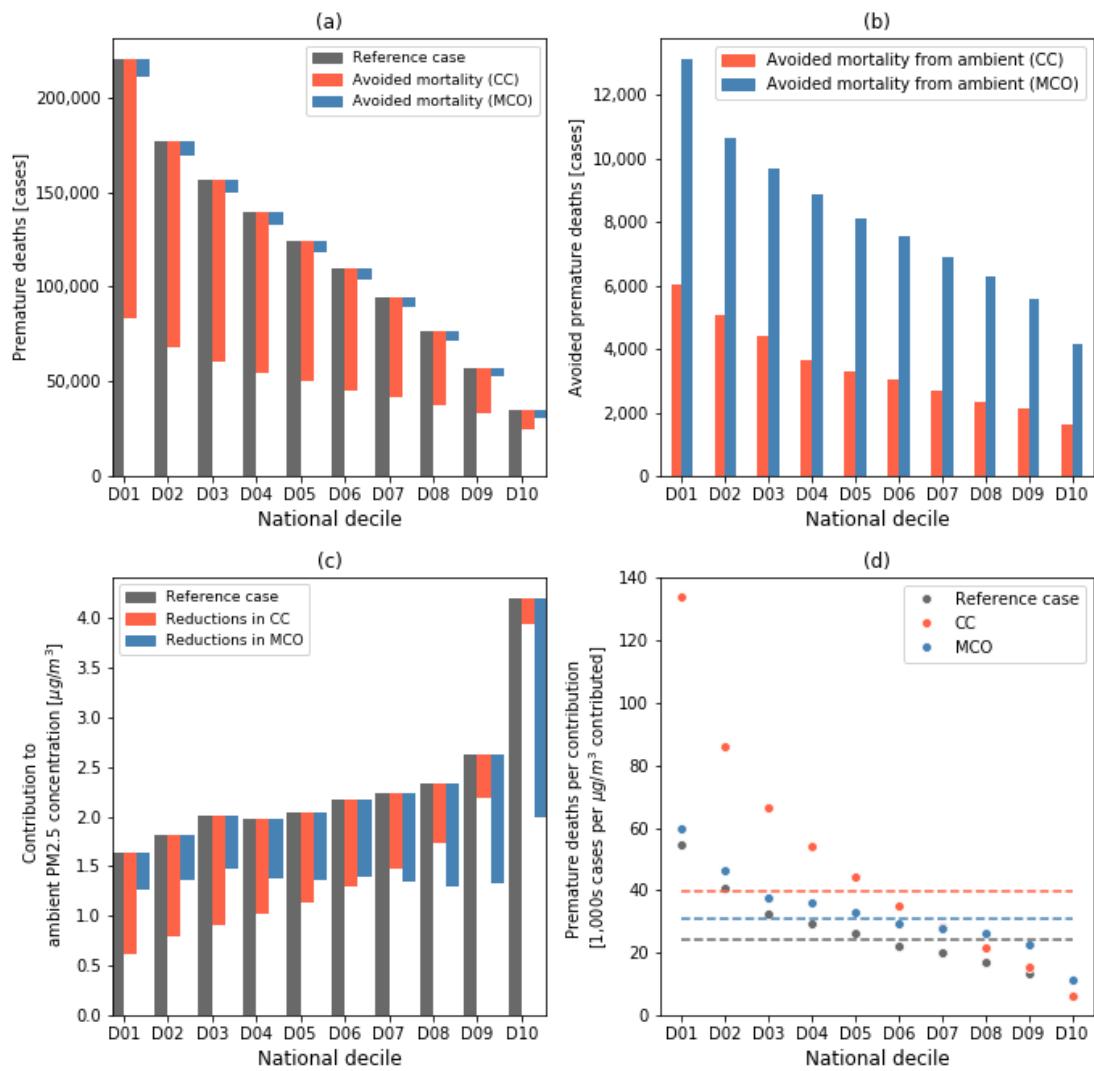


Figure 4 Effect of alternative policies [clean cooking stoves (CC) vs maximum emission controls on all other sources (MCO)] on contributions to and impact of PM_{2.5} pollution by income decile: (a) mortality from ambient and indoor PM_{2.5} by decile (black) and avoided mortality in the two policy scenarios; (b) avoided mortality from AAP relative to the reference case; (c) contribution to ambient PM_{2.5} concentration by decile (black) and reductions in contribution in the two policy scenarios; (d) The PII (mortality from AAP per contribution to ambient PM_{2.5} pollution), per decile for the reference case (black) and for the two policy scenarios; median values are plotted as dashed lines for each scenario.

Discussion and conclusions

Over 150 million solid fuel burning cook stoves were the most lethal source of PM_{2.5}-related emissions in India in 2010, likely causing over 700,000 premature deaths. Due to this high prevalence, there is also a perception that these cook stoves present a public health hazard to others who do not use them. However, in this study we show that cook stoves' contribution to AAP is only 40% of that of other PM_{2.5} sources that are triggered by household consumption. Food production and waste dominate indirect PM_{2.5} emissions by households.

Low-income households face the brunt of all pollution sources – not only do they suffer indoor air pollution from their cooking, but they also face a disproportionate share of mortality risks from AAP, including from indirect PM_{2.5} pollution to which they contribute little. Their cook stoves also impose mortality risks on higher income groups that predominantly use clean fuels, but to a much lower extent. We present a new pollution equity metric of households' mortality risk per unit of their PM_{2.5} pollution. According to this measure, populations in the lowest decile are disadvantaged by a factor of 16 relative to the highest decile.

Policy-wise, due to the dominance of premature deaths from indoor air pollution, providing clean cooking fuels remains the most effective way to reduce premature deaths from air pollution, with low-income households benefitting the most. Industry-wide pollution controls would reduce the number of premature deaths in India by an order of magnitude less. This rather small reduction from controls is for a number of other reasons as well, such as the high share of dust and imported pollution, feasibility constraints in implementation, and the low sensitivity of mortality to reductions in PM at high concentration levels due to the highly non-linear shapes of exposure-response functions used. Though we do not assess the costs of alternative approaches to reducing air pollution in this work, studies show that providing universal access to clean cooking costs an order of magnitude less than controls on other anthropogenic pollution sources.^{20,21} Furthermore, the welfare benefits of reduced air pollution far exceed control costs.^{22–25}

In any case, our study provides a new insight on the relative merits of clean cook stoves versus other emission controls: indirect PM emissions represent more of a public health and environmental justice concern, by imposing disproportionate harm on lower income communities.

Results presented in this study are subject to uncertainties, both in data as well as in some aspects of the methods. In summary (see SI for details): the exposure-response relationships have evolved over the last decade^{26–30}, leading to different mortality estimates. However, our principal findings lie in the distribution of mortality risk and PM contributions, which are unaffected by uncertainty in the absolute values. The income-dependent vulnerabilities are very uncertain and do affect the distribution of impacts, and income is one of many determinants of vulnerability. However, data for non-income factors were unavailable. Uncertainty in atmospheric dispersion and the spatial distribution of some ‘informal’ PM sources, such as municipal waste burning, may impact the distribution of PM concentrations. Their exploration is useful, should data become available.

Our results may underestimate pollution inequities if such sources are concentrated in low-income areas.

As a next step this work could be expanded to other countries for which the required datasets exist, especially for more recent years. The set of scenarios to be analyzed could be refined and additional air pollution control options could be considered in the MCO scenario, such as fuel switches and energy efficiency measures. A forward-looking perspective could be developed, linking up to the scenarios literature, offering additional perspectives on the equity implications of potential future air quality policies.

Methods

Figure 5 provides a logical flow of the methodologies used here to derive both contributions and impact pathways.

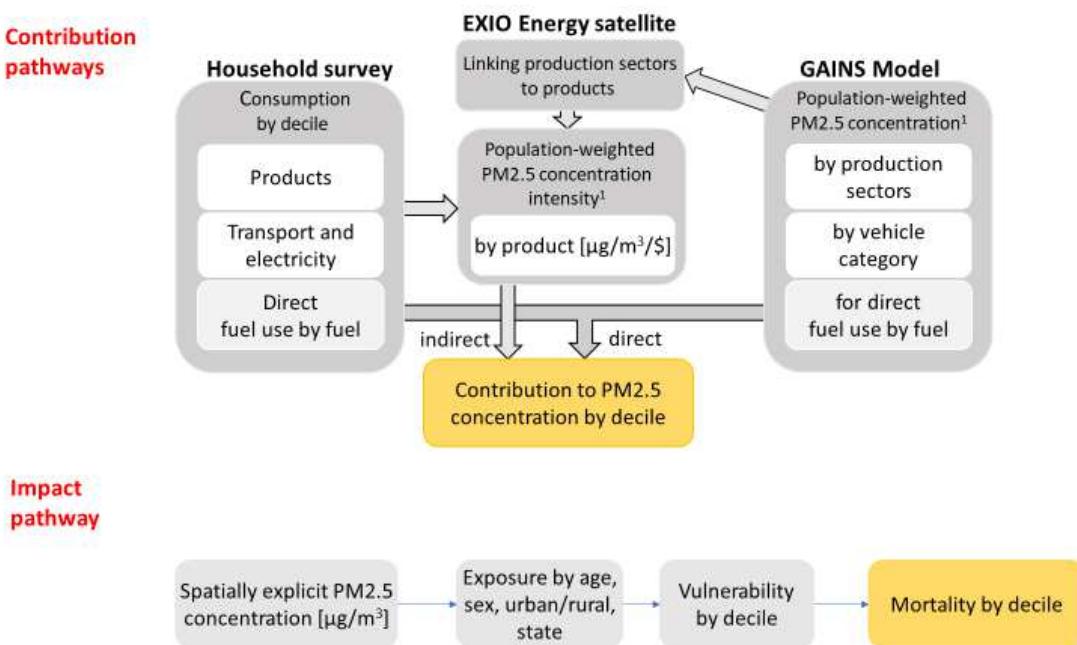


Figure 5 Methods overview. Note 1: all concentration calculations are performed spatially explicit on a 0.1 degree x 0.1 degree grid and are later aggregated to annual, population-weighted national averages.

The analysis of contributions to pollution and mortality by decile consists of four broad steps: (a) calculation of direct emissions of relevant pollutants (primary PM_{2.5} and precursors) and resulting concentrations from households, transport and the production sectors, calibrated to statistics and inventories, at the scale of urban and rural regions by state; (b) converting production sector PM_{2.5} contributions to product contributions via the EXIO energy satellite; (c) mapping the PM_{2.5}

contributions, both direct and indirect, to the income deciles via the consumption patterns derived from the household survey; and (d) determining the mortality associated with exposure to these PM_{2.5} concentrations factoring these households groups' vulnerability to PM_{2.5} pollution. Each of these components is discussed in turn below.

Household PM_{2.5} footprints

Household PM_{2.5} emissions footprints include emissions from: fuel combustion in the home, such as in cook stoves (IPCC's Scope I); fuel combustion outside the home to support households' energy services, such as transport and electricity (IPCC's Scope II); and from the fuel combustion and other industrial processes, including agriculture, that result from the production and delivery of products and services purchased by households (IPCC's Scope III). The GAINS model was used to calculate PM_{2.5} emissions intensities for all sectors in the economy, including household, transport and industry. These sectoral emissions intensities were combined with households' direct or embodied sectoral consumption of products and services from these sectors using a multi-regional input-output database, EXIOBASE linked to the household consumption survey, as elaborated below.

The GAINS model. GAINS (Greenhouse Gas-Air Pollution Interactions and Synergies)¹⁴ is an integrated model for assessing air pollution emissions, ambient pollution concentrations, and their health impacts under different policy scenarios. Emissions are calculated on detailed sectors for all anthropogenic activities related to air pollution or greenhouse gas emissions. A detailed database of technology-specific emission factors is used in conjunction with information on application rates of different emission abatement technologies to calculate production based emissions of PM_{2.5} and its gaseous precursors NOx, SO₂, NH₃, and non-methane volatile organic compounds (VOCs). GAINS calculates emissions at the level of regions, which in India correspond to 23 states and aggregates of smaller states. In this study, the energy balances for all Asian countries are calibrated to IEA statistics for 2010 at national level and downscaled to the region level. Direct household emissions are broken down by income group within GAINS based on household surveys (see below) to quantify the contributions of different income groups to ambient PM_{2.5}, while the contributions from indirect emissions are attributed to households, public sector, and capital stock formation through the input-output database.

The household survey. The data for household's consumption of both direct and indirect sources of PM_{2.5} emissions was obtained from the Indian National Sample Survey (NSS) Organization's Household Consumer Expenditure survey (round 68) from the year 2011-12. The NSS dataset covers a nationally

representative sample of households from across the country and collects information on the quantities and expenditures of various household fuels, and other goods and services consumed, as well as details on household demographic and socio-economic characteristics. For Round 68, the sample included 59,695 rural households and 41,967 urban households. The survey aims at generating estimates of household expenditure and the distribution of households and persons over the total expenditure range separately for the rural and urban sectors of the country, for States and Union Territories, and for different socio-economic groups. Besides measuring household expenditure and consumption levels, the survey is also used to derive the budget shares of different commodity groups for the rural and urban population. We used data from the survey specifically on expenditures and quantities of fuels consumed, other expenditures on goods and services, total household expenditure (a proxy for income), household size and location.

Household cooking fuel use. The NSS records data on monthly fuel expenditures and quantities consumed by fuel type. Information on the actual end-use for which each energy type is used is not recorded in the survey. However, data is recorded on the primary source of cooking fuel and lighting fuel. For most fuels the actual end-use for the fuel is self-evident or can be ascertained by combining information from questions related to primary source of lighting and cooking³¹.

Household electricity use. We use data directly from the NSS on monthly household consumption of electricity in kWh for estimating direct electricity use of households.

Household transport use. Our analysis requires households' transport fuel use, including that which is used directly in privately owned vehicles, and what is indirectly used by public transit and taxis. The NSS records households' expenditure on fuel and on public transit, including bus, rail and private taxis. While we could use fuel prices to determine fuel use for households that own vehicles, we would not be able to determine fuel use for public transit, which constitutes over 70 percent of passenger travel. Instead, we estimate passenger-km (p-km) traveled by decile, by using prices of transit, including bus and rail, which are expressed in INR per p-km. We translate vehicle fuel expenditures into p-km using prevailing fuel prices and assumptions of average vehicle efficiency. We then allocate total fuel use in the transport sector to households in proportion to their travel (passenger-km). This is the closest we can come with available data and without making highly uncertain assumptions about bus and rail occupancy rates (to determine their fuel use). Further details can be found in the SI.

I/O Tables and its energy extension (EXIO). We derive a PM_{2.5} extension matrix for EXIOBASE3 based on the PM_{2.5} concentration by GAINS sector, for which we first go through the GAINS-EXIO mapping procedure described below. Then, the PM_{2.5} extension matrix—the outcome of this mapping—provides direct contributions to PM_{2.5} concentration by EXIO sectors in India. Based on this PM_{2.5} extension matrix, embodied PM_{2.5} intensities ($\mathbf{PM}_{\text{int,IO}}$, $\mu\text{g}/\text{m}^3$ per euro) for each IO sector can be derived by

$$\mathbf{PM}_{\text{int,IO}} = \mathbf{S} \cdot \mathbf{L}$$

Where \mathbf{S} is the direct PM_{2.5} matrix dividing the PM_{2.5} contribution of each EXIO industry by its output (also called as a ‘stressor’ matrix in the IO community), and \mathbf{L} refers to the Leontief inverse, which shows the direct and indirect monetary inputs across the supply chain required to produce one monetary unit by each industry.

We then map $\mathbf{PM}_{\text{int,IO}}$ — embodied PM_{2.5} intensities (per monetary unit) categorized by the EXIO industrial classification—to COICOP consumption categories for the ease of aggregation across consumption categories.

$$\mathbf{PM}_{\text{int,COICOP}} = \mathbf{PM}_{\text{int,IO}} \cdot \mathbf{V} \cdot \mathbf{B},$$

where \mathbf{V} represents valuation matrix converting between basic and purchaser price schemes (considering tax/subsidy and transportation/trade margins), and \mathbf{B} is the bridge matrix we developed between the COICOP categories and the IO sectors. The details of this process can be found in our previous study³².

We multiply the household consumption \mathbf{Y}_i by COICOP category for income decile i to $\mathbf{PM}_{\text{int,COICOP}}$, which gives decile i ’s indirect contribution to PM concentration $\mathbf{PM}_{\text{con},i}$ through their household consumption.

$$\mathbf{PM}_{\text{con},i} = \mathbf{PM}_{\text{int,COICOP}} \cdot \mathbf{Y}_i$$

On traded consumption. In our accounting, we allocated only the PM_{2.5} contribution attributable to domestic household consumptions. Domestic industrial PM_{2.5} emissions incurred to manufacture goods to be exported are not accounted in contribution by ‘household consumption’ but by ‘other consumptions’, which is bundled up with ‘capital accumulation’ etc.

We included indirect emissions from imported goods to our calculation, since we had no data separating imported consumption shares for each of the deciles. And we assume that the imported goods consumed by Indian households are assumed to have the same concentration intensity as the domestic goods. This is acceptable given that we find imported goods take only about 3.3% in total household monetary consumption nationwide (based on EXIO household final demand vector). But

we can expect that this will overestimate the domestic contributions from rich deciles, who have higher shares of consumption of imported goods.

Mapping between EXIO industries and GAINS model sectors. In order to establish a sectoral mapping between GAINS sectors and the EXIO industries, we use the EXIO final energy extension developed by Mastrucci et al.³³, which provides information on final energy consumption across various energy carriers and end-use sectors. It covers three main end-uses: transportation, non-transportation, and non-energy. And transportation final energy is broken down to five more sub-categories: road, rail, marine, air, and other. Road transportation energy here is only for industrial purpose, a large part of which is for trucking, and is not including residential/commercial transportation energy.

We made a few simplifying assumptions that allow us to bridge the gap between the different model ontologies. These assumptions include: (i) all fuel use and emissions associated with cars and buses are associated with direct household consumption, while all fuel use and emissions associated with trucks are associated with the industry sectors in the EXIO table. (ii) Matching aggregate sectors and proportional scaling: since in many cases there is no direct mapping between the sectors in EXIO and GAINS, sectors have been aggregated to a level where they can be matched. These 15 sectors include, e.g. services, iron and steel industry, construction, agriculture. Emissions from energy can be calculated in GAINS for different energy carriers. Information from EXIO is then used to allocate these emissions to the EXIO sectors, using the relative fuel uses for each sector and carrier. Thus we assume that within an aggregate sector, the emissions in each EXIO subsector is proportional to the fuel use of the sector within the aggregate sector. (iii) There are other relevant non-energy related emissions (e.g. emissions of NH₃ from livestock farming), which in GAINS are labelled *process-related emissions*. These are mapped to relevant EXIO sectors or are distributed across relevant EXIO sectors. For example, the emissions related to processing of food and fertilizer use are distributed uniformly across relevant sectors.

The mapping of emissions and concentrations between GAINS source categories and the EXIO industries proceeds thus in four steps:

1. separation of the trucking-related emissions/concentrations. We use that all diesel consumption for road transportation in EXIO is related to trucking emissions, so all trucking-related energy consumption is only related to industries and not to direct household

consumption. With this we calculated total emissions from the GAINS categories for light-duty and heavy-duty trucks

2. calculate energy-related emissions/concentrations
3. add process-related emissions/concentrations
4. add trucking-related emissions/concentrations

Emissions calculations. We use the GAINS model for (a) calculating the emissions in each source of several hundred source categories of the Indian emissions inventory and (b) relating emissions from the source categories to concentration and exposure levels (at the grid level and aggregated), as well as associated mortality. In this way we can attribute the anthropogenic part of the population-weighted concentration of (or exposure to and eventually mortality from) PM_{2.5} in India to different sectors/activities in the economy. For (a) air pollutant emissions are calculated for each of the detailed source category as a function of the underlying economic activities, technology-specific emission factors, and the implementation rates of technologies. In other words, for each source the sum of emission factors, weighted by their implementation rates results in an average emission factor that represents the overall stringency of the emission control policy.

Calculation of ambient PM_{2.5}. Ambient concentration calculations used in this study follow the methodology described by Amann et al. (2020)¹⁴. The general principle of ambient PM_{2.5} calculations in GAINS has been discussed by Amann et al.¹³. Ambient PM_{2.5} is calculated on a 0.1° grid from emissions of PM_{2.5}, SO₂, NO_x, HN₃, and VOCs by applying a linear approximation of the EMEP Chemistry Transport Model. More details can be found in the SI.

Calculation of premature deaths from AAP. As shown by epidemiological studies, exposure to elevated concentrations of PM_{2.5} is associated with an increased probability to die from cardiovascular and pulmonary diseases³⁴. We follow here the methodology developed in the framework of the Global Burden of Disease (GBD) studies^{27,30,35}, which assumes integrated exposure response curves relating PM exposure to mortality from ischemic heart disease, chronic obstructive pulmonary disease, acute lower respiratory infections, lung cancer, and stroke.

To assess the increased risk of mortality from elevated PM_{2.5} concentrations, we use disease specific integrated exposure response functions developed by the Global Burden of Disease (GBD) 2013 study^{30,36}, which were updated from those used in GBD 2010²⁸ and have been used by the WHO in

their most recent assessment of health burdens from global ambient air pollution³⁶. All calculations are done specific to disease, age, urban/rural residence, and income.

For the sake of simplicity, the assumption is made that the exposure levels to ambient air pollution depend only on the geographical location but not on income group (in other words, different income groups have the same geographical distribution pattern), which is likely to overestimate health burdens of the high-income population who spends their time mostly in air-conditioned (and hence cleaner) environments, while the exposure of the low-income population is likely underestimated as concentration levels tend to be higher in low-income areas with increased solid fuel use for cooking and more open waste burning in the absence of an efficient collection system.

The population attributable fraction PAF_{dja} of air-pollution related deaths from disease d in region j , urban/rural residence z and age a is calculated as

$$PAF_{dja} = \frac{\sum_m \frac{pop_{jzm}}{pop_{jz}} (RR_{dam} - 1)}{1 + \sum_i \frac{pop_{jzm}}{pop_{jz}} (RR_{dam} - 1)} \quad (1)$$

where m represent the 0.1° grid cells hosting population pop_{jzm} belonging to region j and urban/rural residence z . RR_{dam} is the disease and (possibly) age specific relative risk as calculated from the integrated exposure response functions for PM_{2.5} concentration levels in that spatial unit.

Deaths attributable to ambient PM_{2.5} exposure are calculated by multiplying the PAF_{dja} from Eq. (1) with age specific baseline cases of deaths d_{dja} from disease d in region j

$$pd_{dja} = PAF_{dja} \cdot d_{dja} \quad (2)$$

Age-specific numbers of deaths from individual diseases are estimated from published numbers for the year 2010 in the Global Burden of Disease 2013 project, which were obtained from the GBD data query tool. Age-specific projected total deaths for India are taken from the UN World Population Prospects 2017 and downscaled by population to GAINS region.

In the standard calculations in the GAINS model, baseline disease-age specific mortality is assumed to be independent of the socioeconomic status, which may underestimate health impacts on low-income groups who have less access to health care services. To overcome this possible deficiency, a sensitivity

version of the methodology has been developed for this study which applies disease specific income dependencies to the baseline mortality.

Though there seems to be general agreement in the literature that the lower income population is more vulnerable to many diseases due to more unhealthy lifestyles and less access to healthcare, studies giving hard numbers for differentials in vulnerability are scarce. Chowdhury and Dey⁹ have attempted a quantification of the income dependence of baseline mortalities from three diseases (COPD, IHD, stroke) associated with PM_{2.5} exposure. We use the coefficients developed in their study relating per-capita GDP and baseline mortality to scale the baseline disease specific mortality rates used in our calculation and derive relative shares between income groups.

We assume that a similar relationship between per-capita GDP and mortality as derived for different states in India can be applied to individual income groups. Mean income in each decile is first converted to per-capita GDP in Indian Rupees, then we calculate deaths in each national income decile as

$$d_{COPD,i} = \left(\frac{G_i}{0.113 \cdot 10^8} \right)^{-1.087} \cdot \frac{pop}{10^5}$$

$$d_{IHD,i} = \left[\left(\frac{G_i}{8.9 \cdot 10^8} \right)^{-0.529} - 1 \right] \cdot \frac{pop}{10^5}$$

$$d_{STROKE,i} = \left(\frac{G_i}{2.16 \cdot 10^8} \right)^{-0.575} \cdot \frac{pop}{10^5}$$

Where G_i is the per-capita GDP in income decile i .

We note that the relationships between per-capita GDP and mortality are uncertain and not originally derived for individual income groups, and they are not age specific. We therefore use the numbers of deaths calculated from these relationships only for deriving the relative shares of deaths between income groups. Totals are kept consistent with the estimated age- and disease specific deaths in GAINS. For the two diseases not covered by the income-dependent relationships, equal mortality is assumed between income groups.

Calculation of premature deaths from HAP

For household air pollution as well, the attributable fraction of deaths is calculated by disease and age. We derive risk factors for mortality from each of the diseases from the same integrated exposure-response functions for typical indoor concentrations solid fuel users are exposed to. Measurements report a wide range of indoor concentrations; in line with Smith et al³⁷ we use an assumed mean

concentration of $300\mu\text{g m}^{-3}$. Our calculations do not distinguish gender, although there is evidence that women bear an unequally higher burden of indoor air pollution as they spend more time in the kitchen. The income dependency of baseline mortality rates is taken into account in the same way as for AAP. A population attributable fraction of deaths from disease d at age a is calculated for the population using solid fuels, pop_{SF} in each region j , residence z , as

$$PAF_{HAP,djza} = \frac{\frac{\text{pop}_{SFjz}}{\text{pop}_{jz}}(RR_{HAP,da} - 1)}{1 + \frac{\text{pop}_{SFjz}}{\text{pop}_{jz}}(RR_{HAP,da} - 1)}$$

Combination of AAP and HAP

In our calculations, AAP and HAP are treated as independent risk factors. Attributable numbers of deaths are not additive, as a certain number of deaths are related to both of the risk factors. We calculate their combined PAF within each GAINS model region, residence, income group, disease and age group as the share of deaths attributable to neither of these risk factors,

$$PAF_{AP} = 1 - (1 - PAF_{AAP}) \cdot (1 - PAF_{HAP})$$

and the combined number of deaths as

$$pd_{djzai} = PAF_{AP,djzai} \cdot d_{djzai}$$

The pollution inequity index (PII). This is calculated for each decile d as:

$$PII_d = \frac{PD_d}{C_d}$$

Where PD_d is the number of premature deaths from $\text{PM}_{2.5}$ pollution in decile d and C_d is the contribution of decile d to the annual average ambient $\text{PM}_{2.5}$ concentration (at the national scale). The PII thus indicates the number of deaths from the $\text{PM}_{2.5}$ per unit of contribution of to the $\text{PM}_{2.5}$ pollution. While the absolute value has limited informational value, a comparison across the deciles can be useful, as is shown in the main text. The *normalized* version of this index is $nPII_d = PII_d / PII_0$, where PII_0 here is the median national value of the index. This allows us to identify deciles as either advantaged or disadvantaged relative to the national median. Since the population cancels in the ratio of PD_d and C_d , the normalized index can also be calculated for the urban and rural population in the national deciles separately.

The MCO and the CC scenarios. The maximum control scenario (MCO) scenario represents the emissions and air quality situation under the counterfactual assumption that the most advanced and efficient emission control technologies (aka *best available technologies (BAT)*) were implemented to

the maximum extent in India in 2010 (except for household stoves), and we use GAINS to determine what such a counterfactual may look like. To begin with, the GAINS database stores information on emission control technologies for hundreds of different types of emission sources, and in the model emission control policies are represented as implementation rates of technologies, such as scrubbers, filters, catalytic converters, and the like. For example, emission factors at the level of Euro VI is considered the currently best available technology to reduce emissions from gasoline-fueled cars. Measures that change the underlying energy system or consumption patterns (such as renewables or energy efficiency measures) are not considered here. In the MCO scenario the technology implementation rates are set to the maximum level, so that the average emission factors for each source reach the lowest technically feasible level. The maximum implementation for a given source and technology may be limited by technological constraints as well as the natural turnover rate of capital. The actual maximum values for India in 2010 in the counterfactual MCO scenario are based on what are considered maximum feasible values for Germany for the year 2030 in previous studies.³⁸ Thus, we use a technological frontier defined by Germany, but reach it up to 20 years faster than Germany itself. In this way we obtain a highly ambitious but technically plausible alternative air quality scenario. The CC scenario is complementary to the MCO scenario in that here we assume the full replacement of solid fuels for cooking by an emission neutral fuel, while the emission controls for all other sources remain at reference level.

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Figures

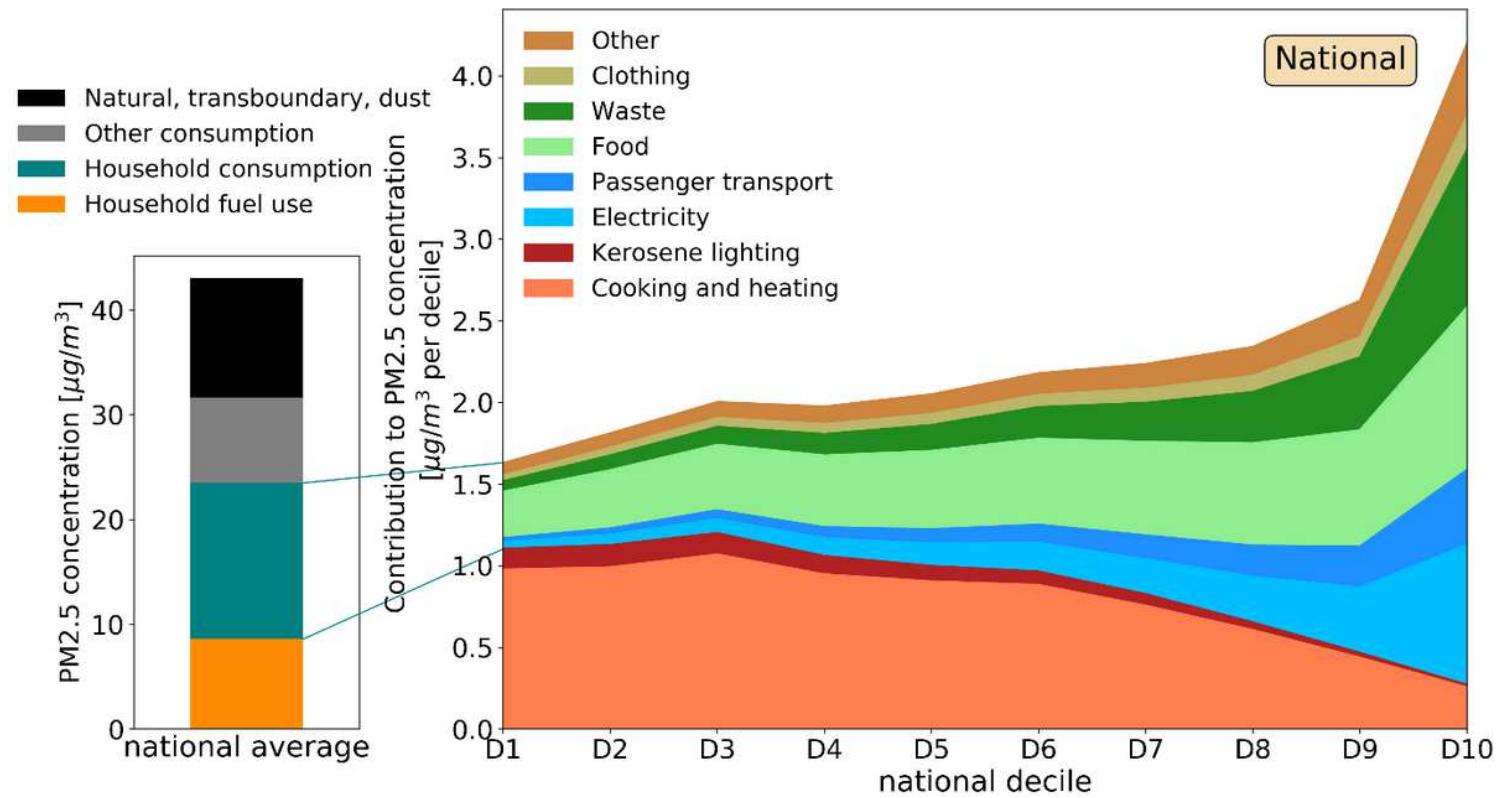


Figure 1

Contribution of consumption patterns to ambient concentration of PM2.5 in 2010. The left panel shows total national PM2.5 concentration by broad source categories. The two blocks at the bottom amounting to around $23\mu\text{g}/\text{m}^3$ are driven by households (orange and dark green: direct contribution from household fuel use and indirect contribution through consumption of goods and services) and are the subject of our analysis. The areas on the right panel break down these two contributing parts into household activities over income deciles. The thin green lines between the two panel indicate which types of activities are classified as 'indirect'.

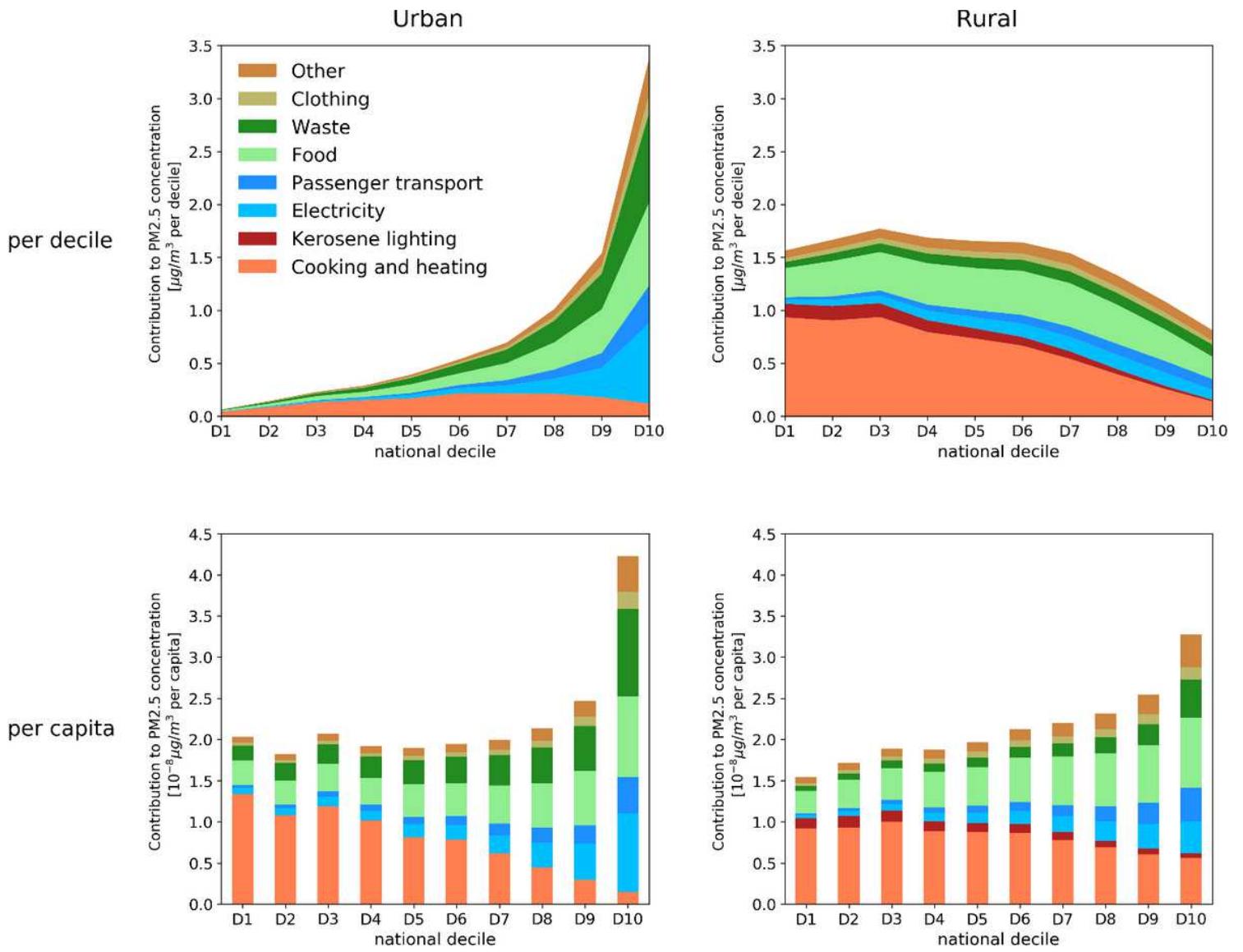


Figure 2

Contribution to ambient PM_{2.5} concentration in 2010 split into urban (left) and rural (right) population. The upper panels show the absolute contribution of urban and rural residents within each national income decile, the lower panels show the per capita contribution. The upper distributions differ because the share of urban vs rural population varies across deciles.

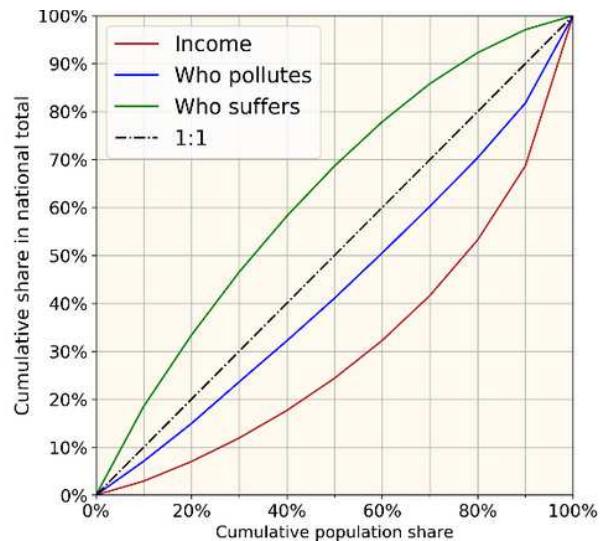
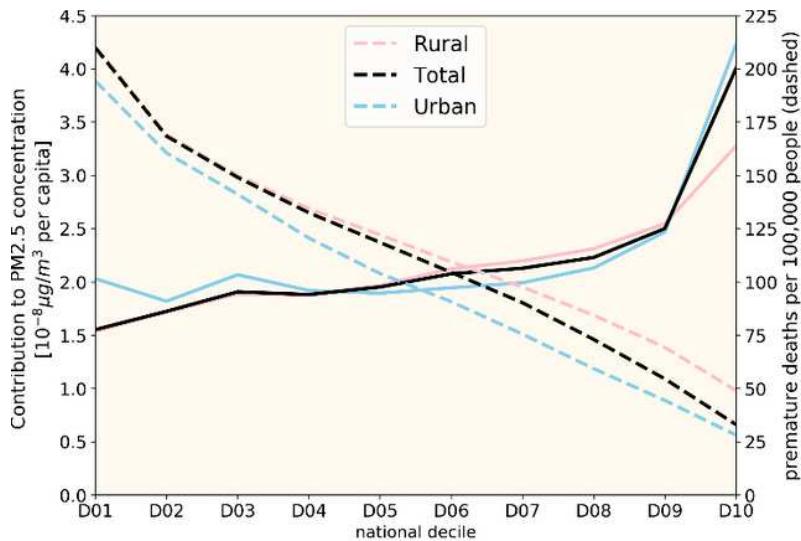


Figure 3

Left panel: Who pollutes (full lines, left axis) and who suffers (dashed lines, right axis) by income decile. The mortality rates, which reflect the income-dependent vulnerability, include effects from ambient as well as from household pollution. Both indicator trends are per-capita. Right panel: Lorenz curve (cumulative population share) of consumption expenditure (“income”), PM_{2.5} contribution (“Who pollutes”) and premature deaths (“who suffers”).

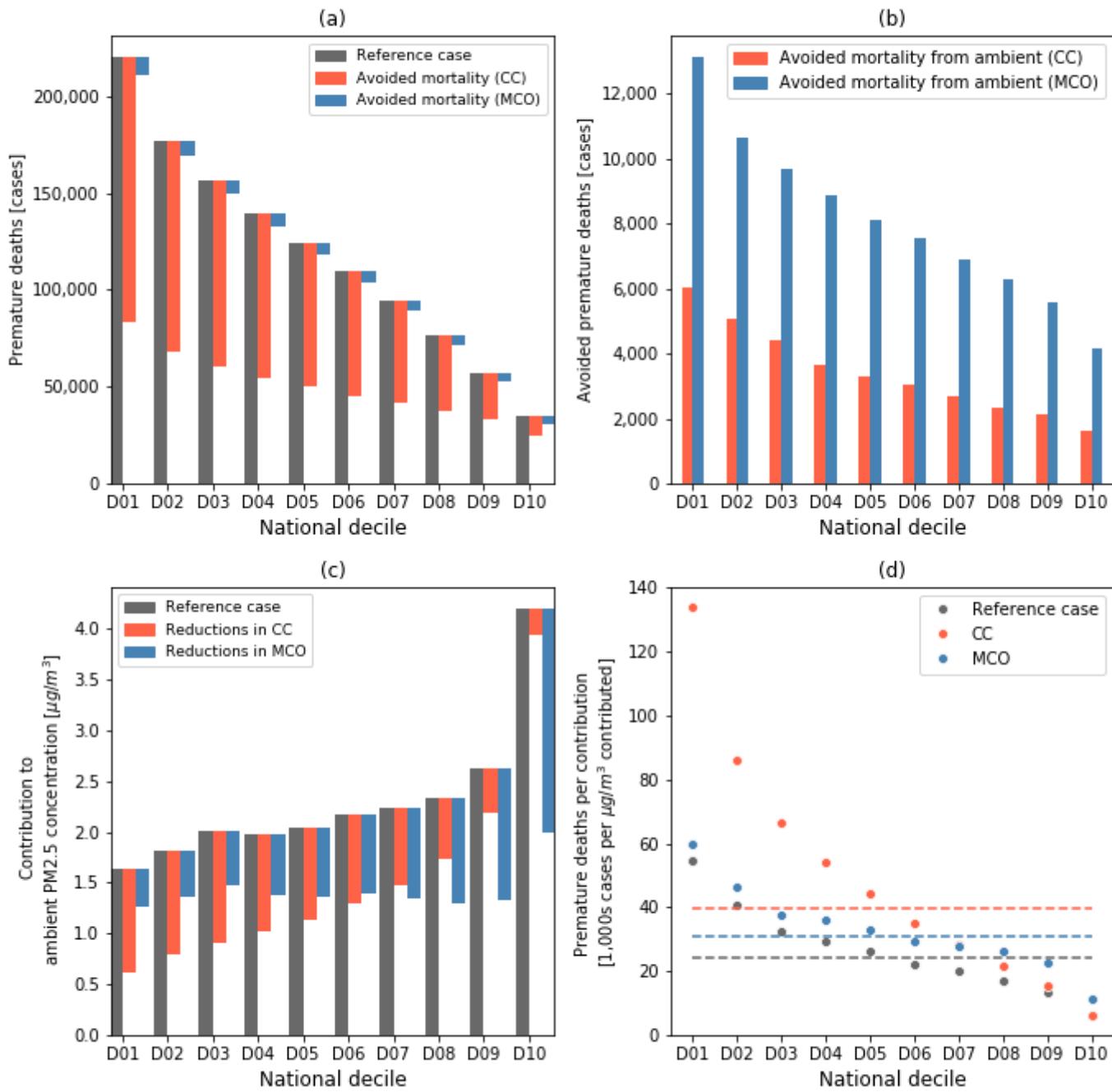
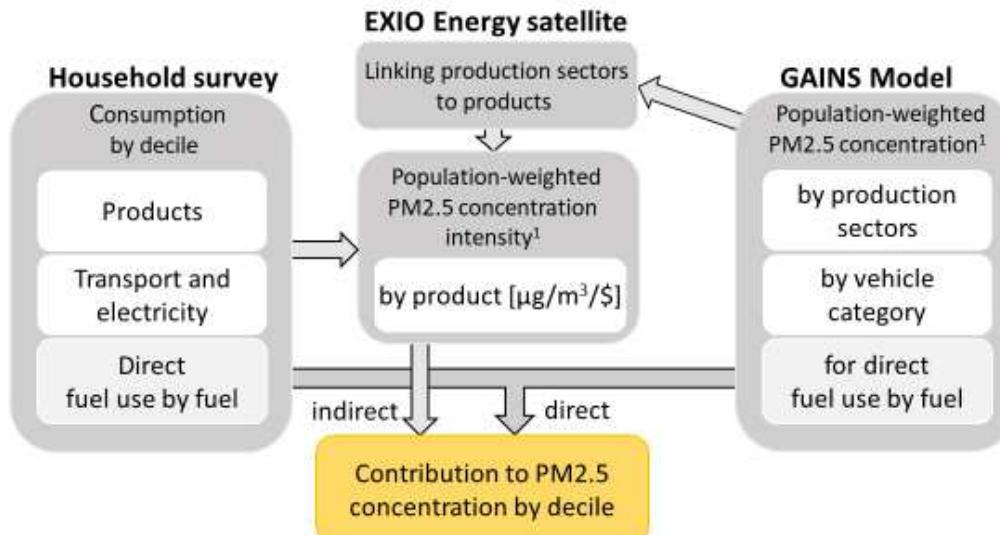


Figure 4

Effect of alternative policies [clean cooking stoves (CC) vs maximum emission controls on all other sources (MCO)] on contributions to and impact of PM2.5 pollution by income decile: (a) mortality from ambient and indoor PM2.5 by decile (black) and avoided mortality in the two policy scenarios; (b) avoided mortality from AAP relative to the reference case; (c) contribution to ambient PM2.5 concentration by decile (black) and reductions in contribution in the two policy scenarios; (d) The PII (mortality from AAP per contribution to ambient PM2.5 pollution), per decile for the reference case (black) and for the two policy scenarios; median values are plotted as dashed lines for each scenario.

Contribution pathways



Impact pathway

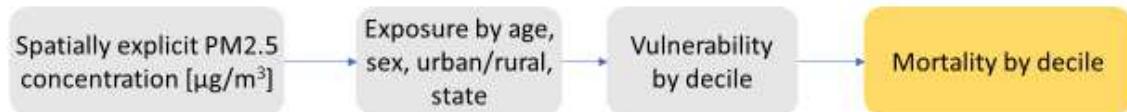


Figure 5

Methods overview. Note 1: all concentration calculations are performed spatially explicit on a 0.1 degree x 0.1 degree grid and are later aggregated to annual, population-weighted national averages.

Supplementary Files

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