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Costs of IQ Loss from Leaded Aviation Gasoline Emissions

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Abstract

In the United States, general aviation piston-driven aircraft are now the largest source of lead emitted to the atmosphere. Elevated lead concentrations impair children's IQ and can lead to lower earnings potentials. This study is the first assessment of the nationwide annual costs of IQ losses from aircraft lead emissions. We develop a general aviation emissions inventory for the continental United States and model its impact on atmospheric concentrations using the Community Multi-Scale Air Quality Model (CMAQ). We use these concentrations to quantify the impacts of annual aviation lead emissions on the U.S. population using two methods: through static estimates of cohort-wide IQ deficits and through dynamic economy-wide effects using a computational general equilibrium model. We also examine the sensitivity of these damage estimates to different background lead concentrations, showing the impact of lead controls and regulations on marginal costs. We find that aircraft-attributable lead contributes to $1.06 billion 2006 USD ($0.01 – $11.6) in annual damages from lifetime earnings reductions, and that dynamic economy-wide methods result in damage estimates that are 54% larger. Because the marginal costs of lead are dependent on background concentration, the costs of piston-driven aircraft lead emissions are expected to increase over time as regulations on other emissions sources are tightened.

INTRODUCTION

Lead is a persistent toxic pollutant that impacts human health and welfare through inhalation and ingestion pathways. Lead emissions from general aviation (GA) piston-driven aircraft are attributable to the addition of tetraethyl lead (TEL) for the formation of aviation gasoline (avgas). GA refers to all civil aviation excluding military and scheduled airline flights. GA flights occur for a variety of purposes including flight instruction, personal or business use, patrol and firefighting, and charter use. The lead additive in avgas prevents piston-driven

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Supporting Information
Expanded methodology including details of the general aviation lead inventory and details of the lead concentration response functions.

engine knock, improves effective fuel octane, and prevents valve seat recession. While lead used as an anti-knock agent in motor vehicles was the largest source of domestic anthropogenic lead emissions from the 1960s through the 1980s, regulations limiting allowable lead concentrations in gasoline in 1985 induced decreases in emissions in the 80s and 90s, and this use of lead was phased out by 1995 in the United States.[1–2] By 2008, piston-driven aircraft emissions accounted for half of all US atmospheric anthropogenic lead emissions, and were the single largest source of lead emissions to the air.[3]

Human exposure to lead can occur through inhalation of lead-containing particles, ingestion of contaminated soil or lead paint, lead from private and public drinking water distribution systems, and through skin absorption.[4] Lead bioaccumulates in human bones, blood, and soft tissue. Lead exposure leads to a variety of deleterious health impacts including disruption of neurological, renal, reproductive, and physical development systems.[5–7] There is sufficient evidence that even low levels of blood lead are associated with neurological impacts in children.[6] Cognitive and neurodevelopmental effects of lead include decrements in IQ tests, lower performance on standardized testing, and decreased graduation rates.[5,6] Other cognitive and behavioral neurological effects include an increase an attention-deficit behavior, conduct problems, memory loss, and poor language performance.[6–8]

In 2006, the environmental nonprofit group Friends of the Earth petitioned the US EPA to regulate or to advance research forming the basis of regulating leaded emissions from GA aircraft. In April 2010, the EPA issued a notice of a proposed rule, describing existing data and planned research and requested comment and further information on the subject.[9] In 2013, the EPA released findings that lead levels were above the National Ambient Air Quality Standards (NAAQS) at two airports. Meanwhile, the FAA has announced its intention to certify and make available an unleaded replacement fuel by 2018.[10]

Eliminating lead from automobile fuel, new residential paint, and plumbing systems over the past several decades likely contributed to significant economic benefits. IQ-related gains in discounted lifetime earnings from reduced lead exposure due to these regulations for a single year cohort of American children have been estimated to be between $110 and $319 billion relative to peak exposure.[11] The potential nation-wide IQ-related benefits of eliminating lead from aviation fuel have not previously been quantified. Previous aviation studies have focused on avgas's contribution to elevated lead levels at individual airports or regions, have excluded emissions from GA cruise, and have not calculated monetized damages, focusing instead on lead concentrations in the atmosphere, soil, or in the blood of exposed children.[3,12,13] In addition to decreasing cohort-wide lifetime earnings, productivity losses from lead related IQ deficits will affect economic output, but the economic feedbacks of lead exposure have not been quantified. Here, we estimate the costs of leaded aviation fuel on society through IQ-related impacts of aviation lead emissions across the United States.

MATERIALS AND METHODS

We developed temporally and spatially resolved aviation lead inventories using piston-driven aircraft data for 2008 including emissions from cruise phase, which have been excluded from prior assessments of aviation-attributable lead concentrations (which only included emissions during takeoffs and landings at specific airports). We develop a model to calculate static costs from lead-related IQ losses using concentration-response functions from literature. We determine the marginal costs of aviation lead for three cases by applying different background concentrations of total suspended lead particulates. Finally, we determine dynamic economy-wide costs associated with IQ losses from lead emissions using a recursive-dynamic general equilibrium model.

Lead Inventory and Emissions Modeling

The total consumption of leaded avgas in the United States in 2008 was 248 million gallons.[14] The most common formulation of avgas supplied in the US is "100 Low Lead" (100LL), which has a maximum lead concentration of 2.12 gPb/gal. Limiting the domain of the analysis to the continental United States, this results in total aviation lead emissions of 539 short tons of lead in 2008. Total lead emissions within the landing and takeoff (LTO) cycle are provided for 2008 by the EPA National Emissions Inventory for nearly 20,000 airports and airfields resulting in 257 short tons of lead emitted in LTO;[15] 2.6% of these emissions occur outside of the continental United States and are excluded, and the NEI inventory assumes that 5% of lead is retained in the engine, engine oil, or the exhaust system. A nationwide seasonal distribution of the GA operations that peaks in May (9.8% of operations) and reaches a minimum in January (6.8% of operations) is applied in accordance with a detailed study of the spatial and seasonal patterns of general aviation.[16] This seasonal pattern is similar to the site-specific GA pattern used in a lead study at Santa Monica Airport;[12] however, regional seasonality may be greater in some areas. We apply a single-peak diurnal profile of operations with operations beginning at 6 AM, peaking at midday, and ending at 10 PM that approximates the temporal profile of operations used in a near-airport lead study.[12] A local sensitivity study on lead dispersion found that annual concentration levels were not sensitive to choice of diurnal profile.[3]

The remaining lead is emitted during the cruise phase of flight. Most GA flights are local (i.e. depart and arrive from the same airport) or are of short-duration. Thus, for the latitudinal and longitudinal distribution of emissions from GA flights, cruise emissions are apportioned across each state in accordance with the percentage of operations that originate in that state according to the methodology of the EPA NEI guidance.[15] We develop a triangular characteristic altitudinal distribution of piston-driven aircraft cruise emissions with a mode of 3000 ft and a peak of 13,000 ft from a study of 71 GA aircraft that cover a range of aircraft type, primary-use purpose, and operational characteristics.[16] These operational characteristics are in line with altitudinal profiles of GA airplanes from December 2007 and June 2008 radar data, which had a modal peak in the 1200–3000 ft altitudinal range and decreasing frequency of flights with increasing altitudinal band.[17]

Background emissions for all atmospheric emissions species including aviation were developed from the U.S. EPA National Emission Inventory for 2005.[18] Total lead emissions from this inventory were scaled to 55% of their initial values to account for the removal of 2005 aviation lead emissions, which were generated using an older EPA inventory methodology and not distributed in a spatially consistent manner. While 2005 background emissions are used as a surrogate for 2008 background emissions, total anthropogenic lead emissions decreased from 1.36 to 0.95 thousand tons per annum in the National Emissions Inventory from 2005 to 2008, a difference in emissions of less than 2% of total annual lead emissions at their 1970s peak. The NEI emissions totals represent changes both to actual emissions and to inventory methodologies; therefore, actual emissions changes from 2005 to 2008 may have be more or less than 0.41 thousand tons.[19]

We use the Community Multiscale Air Quality (CMAQ) modeling system v4.7.1 at a resolution of 36 km × 36 km is used to model aviation emission-attributable lead concentrations in the continental United States.[23] CMAQ is a high- resolution regional air quality model used by the EPA to support regulatory impact assessment. CMAQ has been developed for multi-pollutant and air toxic assessment. Aerosol phase hazardous pollutants are tracked using the multi-pollutant CMAQ model and, while chemically inert, undergo microphysical processes and deposition. Meteorological inputs are provided using the Weather Research and Forecasting (WRF) v3.3.1 model for the year 2005.[20] Initial and boundary conditions for all chemical species are obtained from three-dimensional tropospheric chemistry simulations from the Goddard Earth Observing System of the NASA Global Modeling Assimilation Offices (GEOS-Chem).[21,22] The fate and transport of metals and air toxics have been modeled and validated in using CMAQ using monitor data for several species including lead.[24] We compare our modeled concentrations to monitor data from the United States Environmental Protection Air Quality Data Mart following the methodology of the 2011 National Air Toxics Assessment (NATA).[25]

Emissions-to-IQ Loss Pathway

Population exposure to lead is calculated by overlaying annual average surface concentrations on census data stratified by age group provided by Woods and Poole[26] and previously used in aviation environmental analyses.[27] Lead in ambient air can contribute to several exposure pathways, including direct inhalation, and—once the lead is deposited to the surface—ingestion with indoor or outdoor dust, soil, water, and food. Young children's exposure to ambient lead is predominantly through the ingestion pathway, with lead-based paint ingestion representing up to 70% of US childhood lead exposure in the 2000s.[28,29] Because of these multiple pathways, the relationship between recent ambient lead (PbA) and blood lead (PbB) concentrations can be difficult to determine. Several studies use historical data to develop regression models that estimate the impact of changes in PbA measured in Total Suspended Particulates (TSP) on children's PbB, by controlling for factors that could be predictors for non-recent air pathways, like geographic location, home age, and race/ethnicity.[30–37] Based on these studies, this work considers eight concentration response functions consisting of two functional forms for the PbA (μg/m^3 in TSP) to PbB (μg/dL) relationship. The first relates ln(PbA) to ln(PbB) (ln-ln) according to: $\ln(PbB)=\beta \cdot \ln(PbA)+\gamma$. The ln-ln model results in larger changes in PbB per change in PbA at lower PbA concentrations. The second model linearly relates PbA and PbB (linear) according to: $PbB=\beta \cdot PbA$. For the linear functions, slope values are consistent with ranges developed from case studies using the mechanistic Integrated Exposure Uptake Biokinetic (IEUBK) model of the PbA-PbB relationship.[38]

Concurrent blood lead level measured during childhood is the best predictor of IQ when controlling for other social and environmental variables.[39,40] Four concentration response functions identified by the EPA are used to model the resulting IQ decrements from changes in children's concurrent PbB.[38,41] These models are based on the pooled dataset from the meta-analysis of seven longitudinal cohort epidemiological studies, adjusted for errors identified in an independent re-analysis.[41,39] The four concentration-response functions take different functional forms (log-linear with threshold, log-linear with no threshold and linearization at low levels, two-piece linear with slope change at 5 μg/dL, and two-piece linear with slope change at 3.75 μg/dL) to capture uncertainty in the PbB-IQ relationship. While the EPA includes a concentration-response function with a lower threshold, there is no blood lead level cutoff below which adverse health effects have not been observed.[42] Thus, while we present results for all four blood-to-IQ concentration response functions for comparison, results where the use of a threshold results in no damage estimates are excluded from summary statistics. Further details of the air-to-blood and blood-to-IQ concentration response functions are given in the SI.

While the IQ-related impacts of lead are a function of concentration in TSP, CMAQ modeled lead concentrations have only been validated for PM_{10} and $PM_{2.5}$.[24,25] TSP measurements include particles up to 45 microns in diameter, and therefore can be sensitive to even small concentrations of large coarse particles from lead-containing particles from wind-entrained dust, lead re-emissions, paint dust, and other sources. Thus, for this study, we apply several background TSP concentrations and calculate the aviation-attributable impact as the difference between these background scenarios and the modeled aviation-attributable lead concentrations. The annual maximum 3-month average lead TSP for the United States has decreased from 1.57 μg/m^3 in 1980 to 0.13 μg/m^3 in 2013, a reduction of 94%, based on the average of 12 monitoring sites used in the EPA's Air Trends assessment.[43] Because toxic metal concentrations are expected to vary over small spatial scales,[12,44] and because lead concentrations have decreased dramatically over a short time period, three cases for background lead concentration are modeled: in Case 1, background concentrations reflect average exposure levels of lead TSP; in Case 2, background concentrations reflect measured concentrations from a time before the completed phase out of leaded gasoline; and in Case 3, background concentrations reflect an additional 85% improvement in average air concentration. The 3 Cases were chosen to provide insight into the sensitivity of lead marginal costs given historical data on lead concentrations and exposure levels.

In Case 1, the background annual lead in TSP is fixed at 0.011 μg/m^3, consistent with the measured average lead TSP geographically corresponding to NHANES-participating 1 year-olds between 1999 and 2008.[30] In Case 2, the background annual lead in TSP is 0.4 μg/m^3. This corresponds to the 90th percentile value of the yearly maximum 3-month average lead TSP from the EPA Air Trends study in 2005 and the mean value for 1994 using 12 monitoring sites.[43] This high background case gives an indication of the damages attributable to aviation lead if background concentrations were as high as before the completion of the phase-out of leaded automobile gasoline. In Case 3, the background concentration in TSP is set as the annual PM_{10} lead concentration for each 36 km × 36 km grid cell as the contributions from all sources as modeled in CMAQ. This low background case represents an additional 85% reduction in the average background lead concentrations and highlights the potential change in marginal costs of IQ-related impacts of leaded avgas if background concentrations continue to fall.

Economic Modeling

Following previous studies estimating the economic impacts of lead, we model the earnings reductions associated with IQ loss due to children's lead exposure.[11,45–47] The economic impacts of IQ loss are calculated using two methods: a *static estimate* of the net present value (NPV) of earnings losses for one cohort of 1 year olds, and a *dynamic estimate* that uses cohort-wide earnings losses as an input to labor productivity in a computable general equilibrium model. Following a 1-year cohort is a useful modeling simplification as it provides an indication of the annual costs of aviation-attributable lead emissions as IQ loss correlates best with concurrent blood lead level. These estimates underestimate the total societal impacts of lead exposure, however, as they do not include valuations of other human health impacts, health treatment costs, and damage to wildlife and ecosystem health.

For our *static estimate*, estimates of the percentage change in lifetime earnings associated with an IQ point reduction are taken from both the environmental health and labor economics literature.[11,46,48,49] These estimates take into account both the direct impacts of IQ on wage, and indirect effects of IQ on schooling, and range from 0.9% to 2.37% loss of lifetime earnings per IQ point where productivity is assumed to increase by 1% per annum and future earnings are discounted at 3%. We calculate the NPV of lifetime earnings for a cohort of 1 year olds using earnings data, stratified by age group, from the US Department of Labor's Bureau of Labor Statistics and present results in 2006 USD.

For our *dynamic estimate*, which accounts for the impacts of children's IQ-related earnings loss on the US economy as a whole, we use the US Regional Energy and Environmental Policy (USREP) model. USREP is a recursive-dynamic general equilibrium model of the US economy.[50,51] USREP represents utility-maximizing households and profit-maximizing firms as rational economic agents, and finds the optimal, equilibrium condition of the economy (expressed through commodity prices). Production and consumption depend on the relative prices of different goods, services, and availability of production factors like labor and capital. They are modeled as nested constant elasticity of substitution functions. The availability of labor is based on a household choice between labor and leisure. USREP uses 2006 as a base year. Then, from 2010 onwards, equilibrium conditions are assessed at 5-year intervals.

USREP has been used to explore the dynamic, economy-wide health-related economic effects of climate, energy, and air quality policies including the influence of IQ deficits from mercury exposure.[50–54] Within the model, household labor and leisure are treated as inputs to the good health of the US population. In the case of IQ loss, we consider only the effect of IQ on total lifetime earnings (labor). As pollution increases, more of these inputs are required to "produce" good health, reducing economy-wide productivity by diverting these resources from other sectors. Reduced household productivity results in reduced consumption, with economy-wide ripple effects that compound over time. We therefore express economy-wide losses due to IQ-related effects as changes in consumer welfare, measured as changes to household consumption and leisure.

RESULTS

The contribution of aviation emissions to ambient lead concentrations is calculated by first modeling particulate and toxic species concentrations from all emission sources and then by modeling concentrations for all sources except general aviation. Aviation-induced lead concentrations are estimated as the difference between the two model runs.

The model is validated against monitor data using the approach of the 2011 NATA, using paired comparisons of model concentrations to 22 annual lead monitors of lead PM_{10} observations in 2008.[24] These 22 sites represent all monitors which meet completeness guidelines for determining annual average concentrations of lead PM_{10} in accordance with NATA guidance and are not necessarily representative of the average or range of concentrations of general population exposure. The model, when simulating all anthropogenic lead emissions, has a normalized mean bias of −60% and a normalized mean error of 62% as shown in the left panel of Figure 1. For comparison, a study of 2001 emissions found that modeled lead values had an average normalized mean bias of −48.10% for lead PM2.5 at suburban monitoring stations in January,[24] and CMAQ lead concentrations had a normalized mean error of 154% for PM_{10} in the NATA.[25]

The right panel of Figure 1 shows the concentration of aviation-attributable yearly average surface PM_{10} lead concentrations in μg/m^3. Model results show that GA contributes to a wide dispersion of low concentrations of fine particulate lead emissions. For comparison, the median national total atmospheric surface lead concentration experienced by 1–5 year olds for the same period, based on Air Quality System monitoring data collected with National Health and Nutrition Examination Survey (NHANES) 9908 study participants, is estimated to be 0.011 μg/m^3[29] and fine particulate lead accounted for an average of between 0.0053 μg/m^3 and 0.00723 μg/m^3 of total atmospheric lead at US monitoring sites in July 2001 and January 2001, respectively.[23] The model shows local areas of high aviation lead contributions, particularly the San Diego – Los Angeles Corridor, the Washington – Boston Corridor, and the Dallas/Fort Worth area. Further, the results indicate that aviation contributes to surface lead concentration across the entire continental United States. Because these aircraft-attributable concentrations are small (on the order of 0.0005–0.002 μg/m^3), these contributions may be indistinguishable from background lead concentrations in monitor data. The EPA estimates pristine atmospheric lead concentration at 0.0005 μg/m^3[12] and detection limits and resolution for several monitors are of the same order.[24] However, because there is no known threshold for lead impacts on health, these concentrations may contribute to significant health and welfare impacts.

The *static* IQ-related benefits of controlling all aviation-related lead emissions for Case 1, 0.011 μg/m^3 background lead TSP, are shown in Figure 2. Estimates for annual impacts range from less than 0.01 billion USD to $11.3 billion (2006 USD). Nine estimates return 0 values, all for the log-linear with cutoff blood-to-IQ function. The mean and median benefit of aircraft lead control are 0.95 and 0.51 billion USD per annum respectively for all estimates and 1.06 and 0.60 billion USD per annum respectively for all non-zero estimates. All three linear air-to-blood concentration functions provide lower damage estimates. These linear damage functions are expected to provide conservatively lower damage estimates as they include concentration responses developed from studies with larger lead emissions and blood lead levels.

Case 2 and Case 3 provide insight into the impact of decreasing background lead concentration and regional variability on the IQ-related benefit from controlling lead emissions. Case 2 estimates the impact of aviation lead emissions with background concentrations of 0.40 $\mu g/m^3$ lead TSP. While this concentration is an order of magnitude higher than that of Case 1, 0.40 $\mu g/m^3$ was the mean annual maximum 3-month average lead concentration in the EPA's Air Trends analysis in 1999. The mean and median static aviation lead societal cost for Case 2 are $0.09 and $0.04 billion USD respectively. Whereas in Case 1 the linear air-to-blood concentration response functions provided the lowest cost estimates, in Case 2 they provide higher cost estimates than some ln-ln CRFs as background concentrations are higher.

The *static* benefits of aviation lead control for all three cases are shown in Figure 3. For Case 3, the case with average background concentrations 85% lower than Case 1, the estimated benefits of reducing lead increase to a median of $5.2 billion USD and a mean of $7.9 billion USD. Case 3 produces an upper bound estimate of $51 billion USD, an order of magnitude greater than the median value. As in Case 1, 9 of the 96 cost estimates were $0 values, all for the concentration response function that includes a cut-off value below 1 µg/dL.

In the dynamic case, we estimate the economy-wide impact of children's IQ-related earnings loss by taking the sum of discounted differences between the economic output simulated by USREP considering a cohort of one-year olds exposed to aviation lead emissions and one where aviation lead emissions are eliminated for that cohort. Results of USREP for aviation-attributable lead are shown in Figure 4. The median Case 1 (background lead concentrations of 0.011 $\mu g/m^3$, ln-ln PbA to PbB relationship, dual-linear blood to IQ relationship with inflection at 7.5, and IQ-loss to earnings of 2.37%/IQ point) static estimate is used to explore the impact of economy-wide costs. The economic impact of lead pollution for one childhood cohort starts 15 years after initial emissions as they start to enter the workforce and peaks 50 years later. Because impacts are delayed, results are highly sensitive to discount rate. At a 3% discount rate, dynamic economy-wide impacts of the median Case 1 model are $926 million, an increase of 54% over the static case. At 2% and 7% discount rates, the economy-wide impacts are $1,460 million and $202 million respectively. As shown in Figure 4, at high discount rates, the maximum damages occur when the cohort enters the workforce, but at lower discount rates yearly damages from a single cohort continue to increase for 40 to 60 years.

DISCUSSION

The mean and median Case 1 IQ loss costs of aviation lead emissions are $1.06 and $0.6 billion for static losses and $1.63 and $0.93 billion for dynamic losses. Wolfe et al.[55] estimate the climate and noise damages attributable to US airports at $5.25 billion and $0.63 billion respectively, while Yim et al.[56] estimate air quality damages from ozone and $PM_{2.5}$ in North America as $6.89 billion. Thus, the cost of General Aviation lead emissions are of the same order of magnitude (albeit smaller) than estimated costs of commercial aircraft climate and air quality, but exceed the costs from commercial aircraft noise.

The range of static damage estimates from Case 1 alone spans two orders of magnitude, even after limiting blood-to-IQ relationships to functions without an impact cut-off at low concentrations and only considering one discount rate. This range represents the uncertainty along the exposure-to-impact pathway. Treatment of earnings reduction potential alone provides a factor of 3 differential in damage estimates. While summary statistics presented here focus primarily on the mean and median estimates, the range of damages indicates opportunities for other interpretations. For example, a precautionary approach may focus on the maximum damage estimates ($11.3 billion). Further, expert judgment may be used to down-select exposure-response functions depending on the goal and scope of the analysis. For example, a previous study found that if meta-analyses on lead damages were limited to studies with blood lead levels < 15 μg/dL, levels of the same magnitude as those modeled in this study, the mean of the marginal cost of lead would nearly double.[45] Conversely, considering additional social discount rates and uncertainty from the general equilibrium modeling in the dynamic case would increase the range of damage estimates.

Aviation full-flight emissions contribute to small but impactful increases in lead exposures across the continental United States. Because these contributions may be indistinguishable from background concentrations or lower than monitor resolution detection limits, we use CMAQ to model the contributions from all stages of GA flight to understand the full impact of GA in the continental US. The spatial resolution of CMAQ may lead to an overestimation of lead concentration, exposure, and IQ loss damages further from an airport boundary and an underestimation of lead concentration, exposure and IQ loss damages nearer the airport. Lead emissions are expected to decrease exponentially as a function of distance from a point or area source. Carr et al.[12] found that near-airport lead concentration gradients were indistinguishable from Los Angeles background concentrations at monitor stations further than 900 m downwind from Santa Monica Airport, but did not consider how aviation emissions, such as those from cruise and itinerant operations, contribute to the background. The under-/(over-) estimation of damages nearer (further) from an airport will depend upon the spatial distribution of the local population and the expected contribution of other sources to background lead concentrations. These local airport impacts could be significant.

The results indicate that lead damages attributable to a single source are highly sensitive to emissions from other sources. Between Case 2 and Case 1, a 96% reduction in background lead emissions equates to a 92% increase in median expected societal cost of aviation lead. Case 2 suggests that, as emissions from other sources have decreased dramatically, aviation's impact has become more significant. With logarithmic concentration functions, improvements in overall air quality are expected to lead to increases in the marginal costs of additional emissions.[57] Since 2005 the US has continued to tighten lead controls on lead emitters. In 2013, Doe Run Co.'s smelter in Herculaneum, MO ceased primary lead smelting as sulfur and lead emission stringencies increased. In addition, there is significant regional variation in the background concentration of lead in the US.

There are limitations to the lead modeling approach that may influence the usefulness of results in some contexts. The lead inventory is limited by the sources provided in the EPA National Emissions Inventory. Research suggests that forest fires and lead re-emissions from soil are increasingly important sources of lead to the atmosphere.[58,59] These sources, like aviation, were an insignificant source of airborne lead during the peak of leaded gasoline, but now may be a principal source of emissions in certain regions. Further, leaded paint and paint dust is expected to be the largest contributor to childhood lead exposure, with exposure risk being spatially and demographically heterogeneous.[29] This study does not account for this heterogeneity. The CMAQ domain is also limited to the continental United States, and therefore does not account for over 8 tons of yearly aviation lead emissions in Alaska.

Earnings reductions related to IQ loss are only one effect of lead exposure. High lead levels can lead to damages to the nervous, circulatory, endocrine, and renal systems, which may contribute to health costs and foregone wages.[42] At high blood lead levels, the Centers for Disease Control prescribes medical intervention for heavy metal poisoning that can include oral or intravenous chelation. Lower bound estimates of medical treatment costs from all lead hazards are $11–$53 billion, about 6%–20% of total lead damages.[47] Childhood exposure to lead has also been linked to criminal activity. The environmental hypothesis for crime rates suggests that childhood exposure to lead increases the likelihood of possessing low behavior and cognition self-control and that low-self control is an important predictor of adolescent and adult criminal behavior.[60–62] The direct costs of lead-linked crimes in the US in 2006 are estimated at $1.8 billion, and indirect costs, including treatment for psychological and physical damages may contribute to an additional $11.6 billion in damages.[46]

The three cases in this study explore the sensitivity of results to variability in background atmospheric concentrations, but they do not consider the sensitivity of results to variability in other sources of lead including leaded paint and soil lead or sensitivity of results to changes in meteorology and climate. The impact of aviation lead may be overestimated for populations with significant non-atmospheric sources of lead, but the future impact of aviation lead may be larger than current estimates if controls on non-emission sources are tightened or if the available housing stock with leaded paint decreases. While historically aviation has represented a small percentage of total anthropogenic lead emissions, aircraft emissions will continue to represent a larger and larger percentage of legacy emissions and may contribute to significant soil concentrations and therefore lead re-emissions near an airport with a high concentration of GA traffic. Combining full-flight emissions and transport with local dispersion modeling, utilizing higher spatial resolution modeling of population exposure, and incorporating historical emissions of aviation lead in conjunction with higher-fidelity inventories of anthropogenic, natural, and re-emission sources are important areas of future work that can be used to refine the damage estimates provided in this study.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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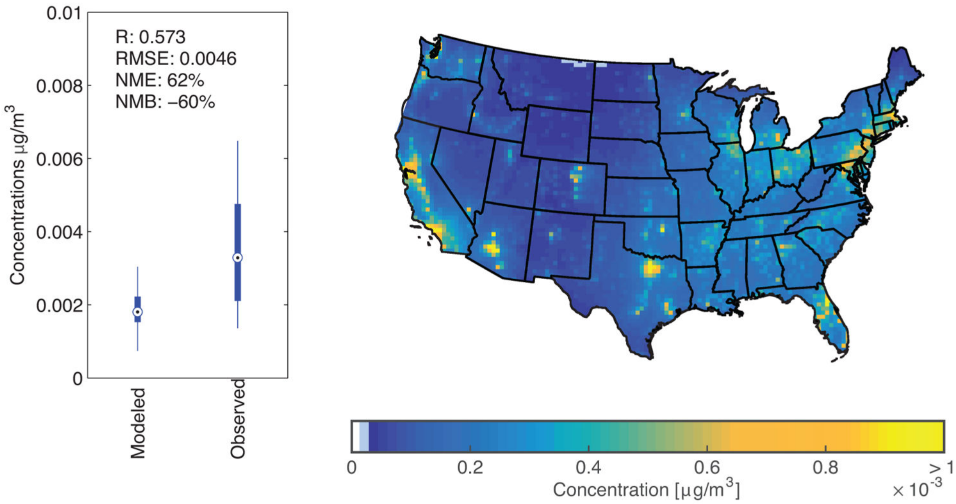

Figure 1.

Left panel: Comparison of simulated all-source anthropogenic emission PM_{10} lead concentrations to observed PM_{10} concentrations. Right panel: Surface atmospheric PM_{10} lead concentrations attributable to aviation in the continental United States ($\mu g/m^3$).

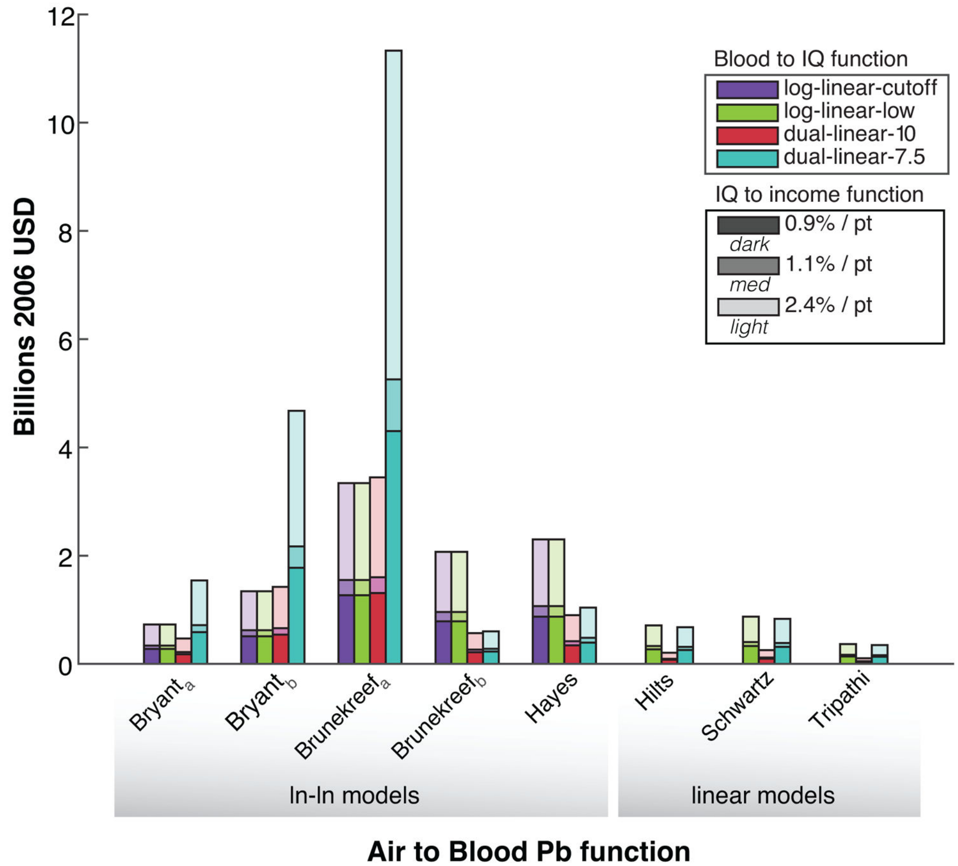

Figure 2.

Static economic benefit of eliminating lead from avgas for 8 Air-to-Blood functions, 4 Blood-to-IQ functions, and 3 different IQ-to-earnings functions for an average background concentration of 0.011 μg/m^3.

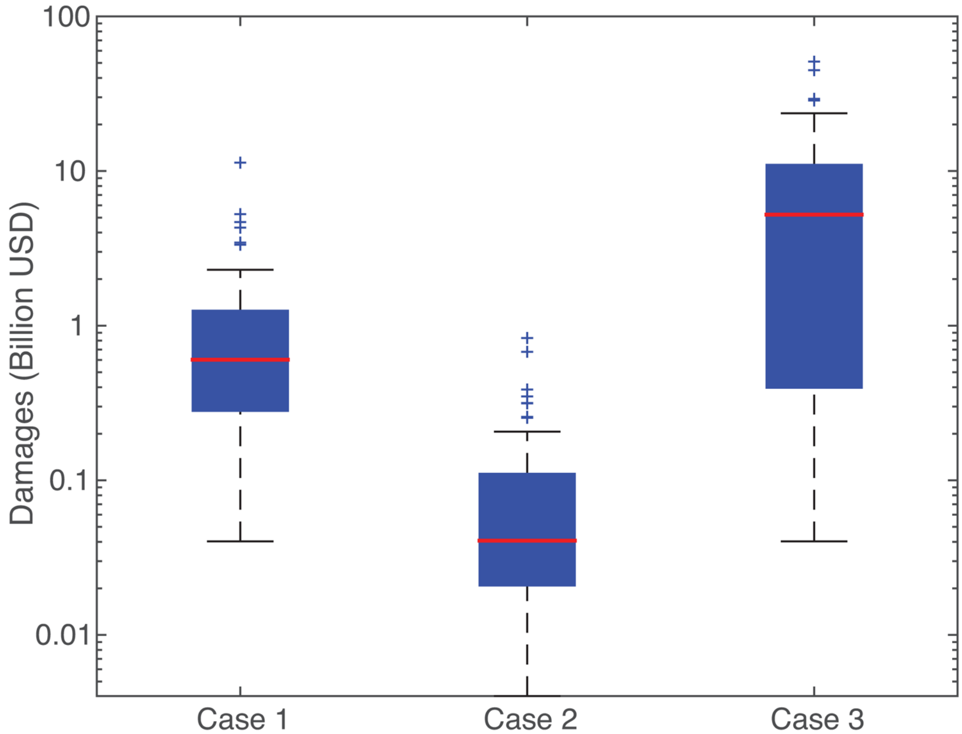

Figure 3.
US-wide IQ-related benefit of aviation lead control, measured as increase in lifetime earnings, for 3 background cases: Case 1: 0.011 μg/m^3, Case 2: 0.4 μg/m^3, and Case 3: a spatially varying case with mean concentration of 0.0017 μg/m^3.

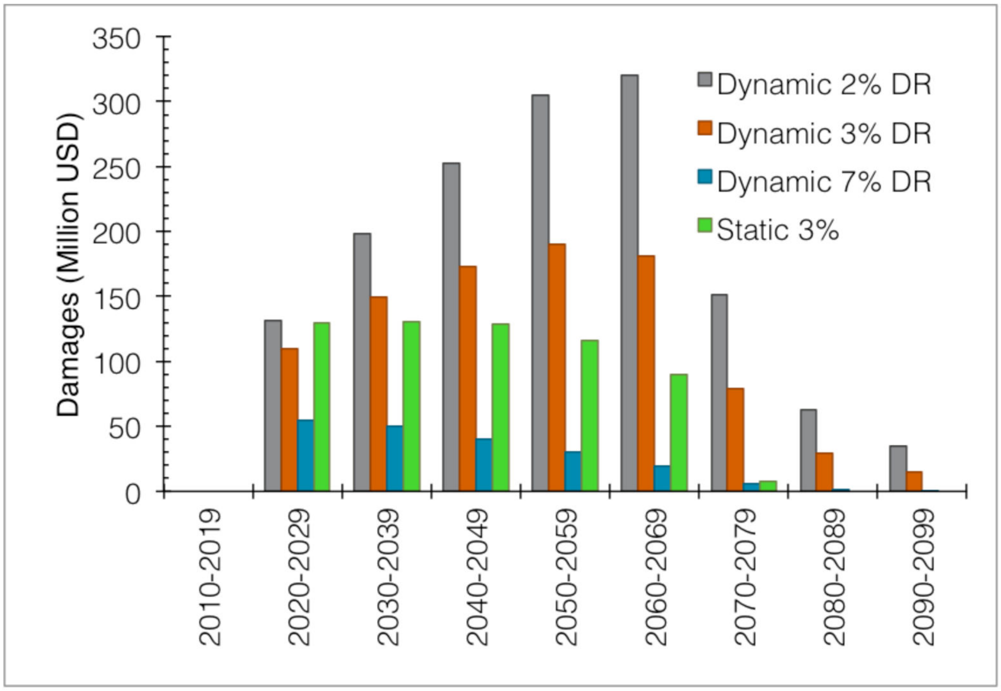

Figure 4.

Present value of lead damages from USREP for a cohort of one-year olds by decade for 3 discount rates compared to the static IQ-loss damage estimates at a 3% discount rate.