Health Effects Institute

NUMBER 221
OCTOBER 2024

RESEARCH REPORT

Assessing the National Health, Education, and Air Quality Benefits of the United States Environmental Protection Agency's School Bus Rebate Program: A Randomized Controlled Trial Design

Sara D. Adar, Meredith Pedde, Richard Hirth, and Adam Szpiro

INCLUDES A COMMENTARY BY THE INSTITUTE'S REVIEW COMMITTEE

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with a Commentary by the HEI Review Committee

Research Report 221
Health Effects Institute
Boston, Massachusetts

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Publishing history: This document was posted at *www.healtheffects.org* in October, 2024.

Citation for report:

Adar SD, Pedde M, Hirth R, Szpiro A. 2024. Assessing the National Health, Education, and Air Quality Benefits of the United States Environmental Protection Agency's School Bus Rebate Program: A Randomized Controlled Trial Design. Research Report 221. Boston, MA: Health Effects Institute.

 Compositor: David Wade, Virginia Beach, VA. Library of Congress Catalog Number for the HEI Report Series: WA 754 R432.

ISSN 2688-6855 (online)

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ABOUT HEI

The Health Effects Institute is a nonprofit corporation chartered in 1980 as an independent research organization to provide high-quality, impartial, and relevant science on the effects of air pollution on health. To accomplish its mission, the Institute

- identifies the highest-priority areas for health effects research
- competitively funds and oversees research projects
- provides an intensive independent review of HEI-supported studies and related research
- integrates HEI's research results with those of other institutions into broader evaluations
- communicates the results of HEI's research and analyses to public and private decision-makers.

HEI typically receives balanced funding from the US Environmental Protection Agency and the worldwide motor vehicle industry. Frequently, other public and private organizations in the United States and around the world also support major projects or research programs. HEI has funded more than 380 research projects in North America, Europe, Asia, and Latin America, the results of which have informed decisions regarding carbon monoxide, air toxics, nitrogen oxides, diesel exhaust, ozone, particulate matter, and other pollutants. These results have appeared in more than 260 comprehensive reports published by HEI, as well as in more than 2,500 articles in the peer-reviewed literature.

HEI's independent Board of Directors consists of leaders in science and policy who are committed to fostering the public–private partnership that is central to the organization. The Research Committee solicits input from HEI sponsors and other stakeholders and works with scientific staff to develop a Five-Year Strategic Plan, select research projects for funding, and oversee their conduct. The Review Committee, which has no role in selecting or overseeing studies, works with staff to evaluate and interpret the results of funded studies and related research.

All project results and accompanying comments by the Review Committee are widely disseminated through HEI's website (*www.healtheffects.org*), reports, newsletters, annual conferences, and presentations to legislative bodies and public agencies.

ABOUT THIS REPORT

Research Report 221, *Assessing the National Health, Education, and Air Quality Benefits of the United States Environmental Protection Agency's School Bus Rebate Program: A Randomized Controlled Trial Design*, presents a research project funded by the Health Effects Institute and conducted by Dr. Sara D. Adar at the University of Michigan School of Public Health, and her colleagues. The report contains three main sections:

The **HEI Statement**, prepared by staff at HEI, is a brief, nontechnical summary of the study and its findings; it also briefly describes the Review Committee's comments on the study.

The **Investigators' Report**, prepared by Adar and colleagues, describes the scientific background, aims, methods, results, and conclusions of the study.

The **Commentary**, prepared by members of the Review Committee with the assistance of HEI staff, places the study in a broader scientific context, points out its strengths and limitations, and discusses the remaining uncertainties and implications of the study's findings for public health and future research.

This report has gone through HEI's rigorous review process. When an HEI-funded study is completed, the investigators submit a draft final report presenting the background and results of the study. Outside technical reviewers and a biostatistician first examine the draft report. The report and the reviewers' comments are then evaluated by members of the Review Committee, an independent panel of distinguished scientists who are not involved in selecting or overseeing HEI studies. During the review process, the investigators have an opportunity to exchange comments with the Review Committee and, as necessary, to revise their report. The Commentary reflects the information provided in the final version of the report.

CONTRIBUTORS

RESEARCH COMMITTEE

David A. Savitz, Chair *Professor of Epidemiology, School of Public Health, and Professor of Obstetrics and Gynecology and Pediatrics, Alpert Medical School, Brown University, USA*

Benjamin Barratt *Professor, Environmental Research Group, School of Public Health, Imperial College London, United Kingdom*

David C. Dorman *Professor, Department of Molecular Biomedical Sciences, College of Veterinary Medicine, North Carolina State University, USA*

Christina H. Fuller *Associate Professor, School of Environmental, Civil, Agricultural and Mechanical Engineering, University of Georgia College of Engineering, USA*

Marianne Hatzopoulou *Professor, Civil and Mineral Engineering, University of Toronto, Research Chair in Transport Decarbonization and Air Quality, Canada*

Amy H. Herring* *Sara & Charles Ayres Distinguished Professor of Statistical Science, Global Health, and Biostatistics and Bioinformatics, Duke University, USA*

Heather A. Holmes *Associate Professor, Department of Chemical Engineering, University of Utah, USA*

Neil Pearce *Professor of Epidemiology and Biostatistics, London School of Hygiene and Tropical Medicine, United Kingdom*

Evangelia (Evi) Samoli *Professor of Epidemiology and Medical Statistics, Department of Hygiene, Epidemiology and Medical Statistics, School of Medicine, National and Kapodistrian University of Athens, Greece*

Alexandra M. Schmidt *Professor of Biostatistics, School of Population and Global Health, McGill University, Canada*

Neeta Thakur *Associate Professor of Medicine, University of California San Francisco, USA*

Gregory Wellenius *Professor, Department of Environmental Health, Boston University School of Public Health and Director, BUSPH Center for Climate and Health, USA *

REVIEW COMMITTEE

Melissa J. Perry, Chair *Dean, College of Public Health, George Mason University, USA*

Sara D. Adar† *Associate Professor and Associate Chair, Department of Epidemiology, University of Michigan School of Public Health, USA*

Kiros T. Berhane *Cynthia and Robert Citrone-Roslyn and Leslie Goldstein Professor and Chair, Department of Biostatistics, Mailman School of Public Health, Columbia University, USA*

Ulrike Gehring *Associate Professor, Institute for Risk Assessment Sciences, Utrecht University, Netherlands*

Michael Jerrett *Professor, Department of Environmental Health Sciences, Fielding School of Public Health, University of California Los Angeles, USA*

Frank Kelly *Humphrey Battcock Chair in Community Health and Policy and Director of the Environmental Research Group, Imperial College London School of Public Health, United Kingdom*

Jana B. Milford *Professor Emerita, Department of Mechanical Engineering and Environmental Engineering Program, University of Colorado Boulder, USA*

Jennifer L. Peel *Professor of Epidemiology, Department of Environmental and Radiological Health Sciences, Colorado State University, and the Colorado School of Public Health, USA*

Eric J. Tchetgen Tchetgen *University Professor and Professor of Biostatistics and Epidemiology, Perelman School of Medicine, and Professor of Statistics and Data Science, The Wharton School, University of Pennsylvania, USA*

John Volckens *Professor, Department of Mechanical Engineering, Walter Scott Jr. College of Engineering, Colorado State University, USA*

HEI PROJECT STAFF

Dan Crouse *Senior Scientist (Study Oversight)*

Allison Patton *Senior Scientist (Report Review)*

Kristin C. Eckles *Senior Editorial Manager*

Hope Green *Editorial Project Manager*

Carol Moyer and Tom Zaczkiewicz *Consulting Editors*

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*Dr. Herring rotated off the Research Committee before this report's publication.

† Dr. Adar is a member of the HEI Review Committee and has been recused from all discussions of the report.

PREFACE

HEI's Accountability Research Program

INTRODUCTION

The goal of most air quality regulations is to protect the public's health by implementing regulatory actions or providing economic incentives that help to reduce the public's exposure to air pollutants. If that goal is met and air pollution is reduced, indicators of public health should improve or at least not deteriorate. Evaluating the extent to which air quality regulations succeed in protecting public health is part of a broader effort — variously termed *accountability research, outcomes research, or research on regulatory effectiveness* — designed to assess the performance of environmental regulatory policies in general. In recent decades, air quality in the United States and Western Europe has improved substantially, and this improvement is attributable to several factors, including increasingly stringent air quality regulations. However, the cost of the pollution-control technologies and mechanisms needed to implement and enforce these regulations is often high. It is, therefore, prudent to ask whether the regulations have in fact yielded demonstrable improvements in public health; results from such investigations can inform future efforts.

In 2003, the Health Effects Institute published Communication 11, a comprehensive monograph on accountability research, titled *Assessing Health Impact of Air Quality Regulations: Concepts and Methods for Accountability Research* (HEI Accountability Working Group 2003). This monograph was written by the members of HEI's multidisciplinary Accountability Working Group after a 2001 workshop to explore this topic raised by NRC (1998) and others. Communication 11 set out a conceptual framework for accountability research and identified the types of evidence required and the methods by which the evidence should be obtained. It has also guided the development of the HEI Accountability Research program, which is discussed below.

Between 2002 and 2004, HEI issued four requests for applications (RFAs), under which eight studies were funded (see **Preface Table**). A ninth study was funded later, under Request for Preliminary Applications (RFPA) 05-3, "Health Effects of Air Pollution." Following this first wave of research, HEI held further workshops to discuss lessons learned, identify key remaining questions, and plan a second wave of research. Those efforts led to further assessments of progress in 2009 and 2010 (HEI 2010a; van Erp and Cohen 2009) and the issuance of RFA 11-1, "Health Outcomes Research — Assessing the Health Outcomes of Air Quality Actions." The first wave of research primarily consisted of studies evaluating relatively short-term, local-scale, and sometimes temporary interventions; RFA 11-1 solicited additional studies with a focus on longer-term, regional- and national-scale regulations, including programs targeted at improving air quality surrounding major ports, as well as further methods development.

This preface describes both the framework of accountability research as it relates to air quality regulations and HEI's Accountability Research program.

BACKGROUND

The first step in assessing the effectiveness of air quality regulations is to measure emissions of the targeted pollutants to see whether they have in fact decreased as intended. To arrive at changes in health that can be attributed to the regulation, additional assessments of air quality, exposure, and inhaled dose are needed, as described in detail below. To quantify past effects on health and to predict future effects (US EPA 1999), some accountability studies have used hypothetical scenarios (comparing estimated outcomes under existing and more stringent regulations) and risk estimates obtained from epidemiological studies. However, more extensive validation of those estimates with data on actual outcomes would be helpful.

The long-term improvements in US air quality have been associated with improved health in retrospective epidemiological studies (Chay and Greenstone 2003; Laden et al. 2006; Pope et al. 2009). Considerable challenges, however, are inherent in the assessment of the health effects of air quality regulations. Different regulations go into effect at different times, for example, and may be implemented at different levels of government (e.g., national, regional, or local). Therefore, their effectiveness needs to be assessed in ways that take into account the varying times of implementation and levels of regulation. In addition, other changes at the same time and place might confound an apparent association between pollution reduction and improved health, such as economic trends (e.g., changes in employment), healthcare improvements, and behavioral changes (e.g., staying indoors when government warnings indicate pollution concentrations are high).

Moreover, adverse health effects that might have been caused by exposure to air pollution can also be caused by other environmental risk factors (some of which might have changed over the same time periods as the air pollution concentrations). These challenges become more pronounced when regulations are implemented over long periods and when changes in air quality and health outcomes are not seen immediately, thus increasing the chance of confounding by other factors. For these reasons, scenarios in which regulations are expected to have resulted in rapid changes in air quality tend to be among the first, and most likely, targets for investigation, rather than evaluations of complex regulatory programs implemented over multiple years. Studies in Ireland by Clancy and colleagues (2002) and in Hong Kong by Hedley and colleagues (2002) are examples of such scenarios.

These inherent challenges are well documented in Communication 11 (HEI Accountability Working Group 2003), which was intended to advance the concept of accountability research and to foster the development of methods and studies throughout the relevant scientific and policy communities. In addition, recent advances in data collection and analytic techniques provide an unprecedented opportunity to improve assessments of the effects of air quality interventions.

THE ACCOUNTABILITY EVALUATION CYCLE

Earlier conceptual frameworks for linking air pollution sources to adverse health effects were further developed in HEI's monograph (HEI 2003) in an expanded framework that is still relevant today. This framework can be used to identify factors along an "accountability evaluation cycle" (see **Preface Figure**), each stage of which affords its own opportunities for making quantitative measurements of the intended improvements.

At the first stage (regulatory action), one can assess whether controls on source emissions have in fact been put into place. At the second stage (emissions), one can determine whether those controls have indeed reduced emissions, whether emitters have changed their practices, and whether there have been unintended consequences. At the third stage (ambient air quality), one can assess whether reductions in emissions have resulted in improved air quality. At the fourth stage (personal or population exposure), one can assess whether the improvement in air quality has reduced people's actual exposure and whether there has been a benefit for susceptible subpopulations (those most likely to experience adverse health effects). At this stage, it is important to consider changes in time–activity patterns that could either increase or reduce exposure. The actual dose that an individual's organs are exposed to should also be considered (i.e., whether reductions in exposure have led to reductions in concentrations in body tissues such as the lung). Finally, at the fifth stage (human health response), one can assess whether risks to health have declined, given the evidence about changes in health outcomes such as morbidity and mortality that have resulted from changes in exposure. The challenge at this stage is to investigate the health outcomes that are most directly related to exposure to air pollution.

At each stage in the accountability evaluation cycle, the opportunity exists to collect evidence that either validates the assumptions that motivated the intervention or points to ways in which the assumptions were incorrect. The collection of such evidence can thus ensure that future interventions are maximally effective.

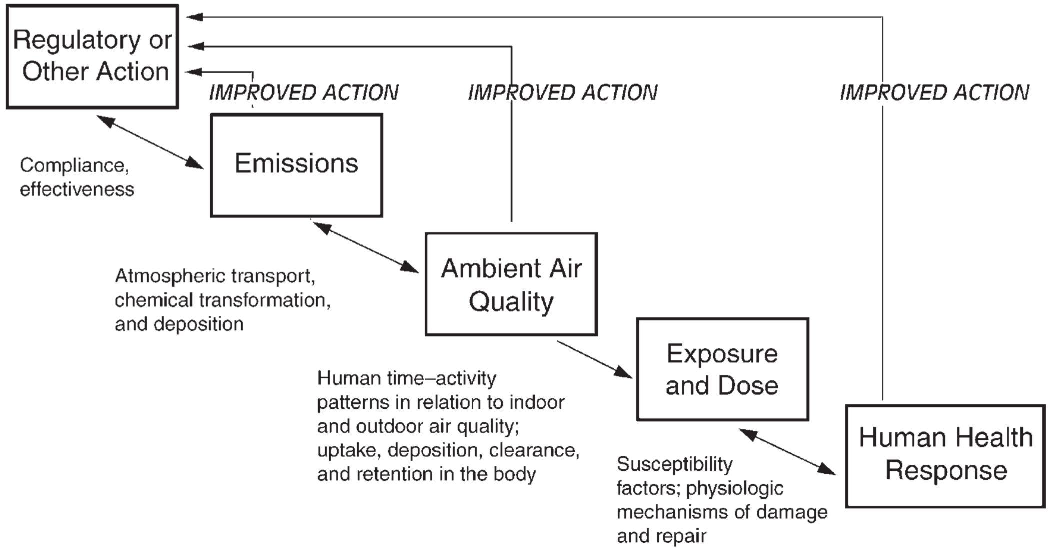
Ultimately, the framework for accountability research will need to encompass investigations of the broader consequences of regulations, not just the intended consequences. Unintended consequences should also be investigated, along with the possibility that risks to public health in fact increased, as discussed by Wiener (1998) and others who have advanced the concept of a portfolio of effects of a regulation.

HEI'S ACCOUNTABILITY RESEARCH PROGRAM

The first wave of HEI's Accountability Research program included nine studies (see Preface Table). These studies involved the measurement of indicators along the entire accountability evaluation cycle, from regulatory or other interventions to human health outcomes. Many of the studies focused on interventions that were implemented over relatively short periods of time, such as a ban on the sale of coal, reductions in the sulfur content of fuels, measures to reduce traffic, and the replacement of old wood stoves with more efficient, cleaner ones. Other studies focused on longer-term, wider-ranging interventions or events; for instance, one study assessed complex changes associated with the reunification of the former East and West Germany, including a switch from brown coal to natural gas for fueling power plants and home-heating systems and an increase in the number of modern diesel-powered vehicles in eastern Germany. HEI also supported research, including the development of methods, in an especially challenging area: assessment of the effects of regulations implemented incrementally over extended periods of time. In one such study, Morgenstern and colleagues (2012) examined changes that resulted from Title IV of the 1990 Clean Air Act Amendments (US EPA 1990), which aimed at reducing sulfur dioxide emissions from power plants by requiring compliance with prescribed emission limitations.

HEI later funded four studies as part of the second wave of its Accountability program (see **Preface Table**). Two studies evaluated regulatory and other actions at the national or regional level implemented over multiple years (Gilliland et al. 2017, Russell et al. 2018); a third study evaluated complex sets of actions targeted at improving air quality in large urban areas and major ports with well-documented air quality problems and programs to address them (Meng et al. 2021); and a fourth study developed methods to support such accountability research (Zigler et al. 2016).

HEI funded a third wave of accountability studies that address an array of regional and national regulatory programs (see Preface Table). As described in their Investigators' Report, the current study by Sara D. Adar and colleagues evaluated the US EPA's School Bus Retrofit and Replacement Program authorized under the Diesel Emissions Reduction Act. They showed that school



Preface Figure. Accountability evaluation cycle. Each box represents a stage in the process between regulatory action and human health responses to air pollution. Arrows connecting the stages indicate possible directions of influence. The text below the arrows identifies factors affecting the effectiveness of regulatory actions at each stage. At several of the stages, knowledge gained from studies on outcomes can provide valuable feedback for improving regulatory or other actions.

attendance and educational achievement had improved in school districts selected for funds to replace old diesel school buses compared to school districts that were not selected for funding. Hystad and colleagues assessed whether air pollution decreases related to cumulative long-term national and local traffic emission-control programs improved birth outcomes among a diverse population of 7.6 million births in Texas between 1996 and 2016. Harper and Baumgartner and colleagues examined the impact of a coal heating ban and heat pump subsidy program in villages surrounding Beijing, China, on air quality, air pollutant exposure, and markers of respiratory and cardiovascular health among 1,000 participants from an existing cohort. This study seeks to identify specific mechanisms by which the coal ban might have improved health by investigating physical, social, and behavioral influences as mediating factors. Kinney and colleagues investigated sweeping air pollution control policies that began in 2013 across multiple regions of China. They seek to show a causal link between regulations, emissions, ambient air pollution, and mortality over a 10-year period. Funded under a separate RFA, Hakami and colleagues created a source- and location-specific database of mortality benefits per ton of primary $PM_{2.5}$, NO_x, SO_2, and ammonia emissions reductions. They showed that emissions reductions in larger cities, particularly primary $PM_{2.5}$, could elicit health benefits nationwide (Hakami et al. 2024).

HEI also continues to fund accountability studies under various other RFAs. A study by Stefanie Ebelt, David Rich, and colleagues was funded under RFA 20-1A *Health Effects of Air Pollution* and is evaluating the effect of selected policies that targeted emissions from motor vehicles and electricity generating units on air quality in Atlanta, New York City, and Los Angeles. Under RFA 20-1B *Air Pollution, COVID-19, and Human Health*, Kai Chen of Yale University and colleagues conducted a multicountry study to evaluate whether changes in mortality are associated with changes in ambient NO_2 and $PM_{2.5}$ levels before, during, and after COVID-19 lockdowns in China, Germany, Italy, and the United States.

Two other accountability-focused studies were recently funded under the *Walter A. Rosenblith New Investigator Award*. In 2022, Lucas Henneman of George Mason University was funded to estimate the impacts of different emissions sources on daily patterns and concentrations of $PM_{2.5}$ at a fine spatial resolution in the United States. He will perform an environmental justice accountability analysis of source-related exposure reductions to determine how such reductions have been distributed across population groups. In 2023, a study by Rachel Nethery of Harvard University was funded to develop statistical methods for characterizing spatial and racial and ethnic variation in health effects associated with exposure to $PM_{2.5}$ across the United States and to design potential policies for reducing $PM_{2.5}$-attributable health inequities.

A complete list of accountability studies funded by HEI to date is summarized in the Preface Table. The first-wave studies are described in more detail in an interim evaluation of the HEI Accountability Research program (van Erp and Cohen 2009; van Erp et al. 2012). An updated interim discussion of HEI's recent experiences in accountability research is also available (Boogaard et al. 2017).

FUTURE DIRECTIONS

The second and third waves of accountability research were conceived and prioritized during HEI's Strategic Plans for 2010–2015 (HEI 2010b) and 2015–2020 (HEI 2015). In its current Strategic Plan for 2020–2025 (HEI 2020a), HEI seeks to continue its leadership role in accountability research by prioritizing opportunities for studies that evaluate what methods are best suited to assess the effectiveness of further air-quality improvements. We envision that future studies will again focus

Preface Table. HEI's Accountability Research Program

Investigator (Institution)	Intervention	Study or Report Title
	First-Wave Studies	
RFA 02-1		
Douglas Dockery (Harvard T.H. Chan School of Public Health, Boston, MA)	Coal ban in Irish cities	Effect of Air Pollution Control on Mortality and Hospital Admissions in Ireland (Research Report 176; 2013)
Annette Peters (Helmholtz Zentrum München–German Research Center for Environment and Health, Neuherberg, Germany)	Switch from brown coal to natural gas for home heating and power plants, changes in motor vehicle fleet after reunification of Germany	The Influence of Improved Air Quality on Mortality Risks in Erfurt, Germany (Research Report 137; 2009)
RFA 04-1		
Frank Kelly (King's College, London, UK)	Measures to reduce traffic congestion in the inner city of London	The Impact of the Congestion Charging Scheme on Air Quality in London: Part 1. Emissions Modeling and Analysis of Air Pollution Measurements. Part 2. Analysis of the Oxidative Potential of Particulate Matter (Research Report 155; 2011)
RFA 04-4		
Frank Kelly (King's College, London, UK)	Measures to exclude most polluting vehicles from entering greater London	The London Low Emission Zone Baseline Study (Research Report 163; 2011)
Richard Morgenstern (Resources for the Future, Washington, DC)	Measures to reduce sulfur emissions from power plants east of the Mississippi River	Accountability Analysis of Title IV Phase 2 of the 1990 Clean Air Act Amendments (Research Report 168; 2012)
Curtis Noonan (University of Montana, Missoula, MT)	Wood stove change-out program	Assessing the Impact of a Wood Stove Replacement Program on Air Quality and Children's Health (Research Report 162; 2011)
Jennifer Peel (Colorado State University, Fort Collins, CO)	Measures to reduce traffic congestion during the Atlanta Olympics	Impact of Improved Air Quality During the 1996 Summer Olympic Games in Atlanta on Multiple Cardiovascular and Respiratory Outcomes (Research Report 148; 2010)
Chit-Ming Wong (University of Hong Kong)	Measures to reduce sulfur content in fuel for motor vehicles and power plants	Impact of the 1990 Hong Kong Legislation for Restriction on Sulfur Content in Fuel (Research Report 170; 2012)
RFPA 05-3		
Junfeng (Jim) Zhang (University of Medicine and Dentistry of New Jersey, Piscataway, NJ)	Measures to improve air quality during the Beijing Olympics	Cardiorespiratory Biomarker Responses in Healthy Young Adults to Drastic Air Quality Changes Surrounding the 2008 Beijing Olympics (Research Report 174; 2013)
	Second-Wave Studies	
RFA 11-1		
Frank Gilliland (University of Southern California)	California and federal programs to improve air quality, including control of emissions from diesel engines and other sources targeted at freight transport and ports, as well as stationary sources	The Effects of Policy-Driven Air Quality Improvements on Children's Respiratory Health (Research Report 190; 2017)
Ying-Ying Meng (University of California Los Angeles)	2006 California Emissions Reduction Plan for Ports and Goods Movement to control emissions from road, rail, and marine transportation, focusing on the ports of Los Angeles and Long Beach	Improvements in Air Quality and Health Outcomes Among California Medicaid Enrollees Due to Goods Movements (Research Report 205; 2021)

Continues next page

Preface Table. HEI's Accountability Research Program (*Continued*)

Investigator (Institution)	Intervention	Study or Report Title
Armistead Russell (Georgia Institute of Technology)	Programs to control emissions from major stationary sources and mobile sources in the Southeast United States	Impacts of Emission Changes on Air Quality and Acute Health Effects in the Southeast, 1993–2012 (Research Report 195; 2018)
Corwin Zigler (Harvard T.H. Chan School of Public Health)	National regulations to improve air quality focusing on State Implementation Plans for particulate matter	Causal Inference Methods for Estimating Long-Term Health Effects of Air Quality Regulations (Research Report 187; 2016)
	Third-Wave Studies	
RFA 17-2		
Amir Hakami (Carleton University, Canada)	Transportation emission reductions in the United States and Canada	Estimating Model-Based Marginal Societal Health Benefits of Air Pollution Emission Reductions in the United States and Canada (Research Report 218, 2024)
RFA 18-1		
Sara D. Adar (University of Michigan)	School bus retrofit and replacement program in the United States	Assessing the National Health, Education, and Air Quality Benefits of the United States Environmental Protection Agency's School Bus Rebate Program: A Randomized Controlled Trial Design (Current Report)
Sam Harper and Jill Baumgartner (McGill University, Canada)	Coal ban and heat pump subsidy program in the Beijing, China, region	How Do Household Energy Interventions Work? (In Review)
Perry Hystad (Oregon State University)	National and local traffic emissions control measures in Texas	The TRANSIT Accountability Study: Assessing Impacts of Vehicle Emission Regulations and Local Congestion Policies on Birth Outcomes Associated with Traffic Air Pollution (In Review)
Patrick L. Kinney (Boston University)	Major national air pollution control regulations in China	Accounting for the Health Benefits of Air Pollution Regulations in China, 2008–2020 (In Review)
RFA 20-1A		
Stefanie Ebelt (Emory University) and David Rich (University of Rochester Medical Center)	Transportation and electricity generation emissions reductions in three US cities	Environmental and Health Benefits of Mobile Source and Electricity Generating Unit Policies to Reduce Particulate Pollution (Ongoing)
RFA 20-1B		
Kai Chen (Yale University)	COVID-19 pandemic lockdowns in China, Germany, Italy, and the United States	Effect of Air Pollution Reductions on Mortality During the COVID-19 Lockdown: A Natural Experiment Study (In Review)
Walter A. Rosenblith New Investigator Award		
Lucas Henneman (George Mason University)	Source-specific emission reductions in the United States	Air Pollution Source Impacts at Fine Scales for Long-Term Regulatory Accountability and Environmental Justice (Ongoing)
Rachel Nethery (Harvard University)	Health inequity policy design in the United States	Designing Optimal Policies for Reducing Air Pollution-Related Health Inequities (Ongoing)

RFA = request for application; RFPA = request for preliminary application.

on large-scale, complex regulations to improve air quality. We will continue to develop and implement statistical methods, particularly those within a causal inference framework, to tackle these complicated questions. In 2023, HEI issued RFA 23-2, *Assessing Changes in Exposures and Health Outcomes in Historically Marginalized and Environmentally Overburdened Communities from Air Quality Actions, Programs, or Other Interventions*, to fund studies that focus on actions to improve air quality targeted at historically marginalized communities in the United States. The selected studies are starting in 2024.

Throughout its portfolio, HEI emphasizes the importance of data access and transparency because they underpin high-quality research that is used in policy settings. Thus, HEI continues to provide other researchers with access to extensive data and software from HEI-funded studies (see *https://www.healtheffects.org/research/databases*). In the same spirit, the State of Global Air website (HEI 2020b) makes available data on air quality and health outcomes for countries around the world. The interactive site allows exploration of the data and comparisons among countries. The data currently cover 1990–2020 and are updated as new data become available.

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HEI STATEMENT

Synopsis of Research Report 221

Evaluation of a Program to Replace Old Diesel-Powered School Buses

BACKGROUND

Air pollution accountability research evaluates the extent to which policies aimed at improving air quality produce the intended reductions in pollutant concentrations and improvements to public health. A major challenge in this research field is isolating changes that can be attributed to the policy in question from changes that might be due to other unrelated regulations or long-term trends. This challenge is a particular concern when policies target numerous pollutant sources, affect large geographic regions, and take several years to fully implement.

Dr. Sara D. Adar of the University of Michigan and colleagues proposed to evaluate a United States Environmental Protection Agency program for funding to replace or retrofit old school buses that was implemented under the Diesel Emissions Reduction Act. This nationwide program, which was piloted in 2012 and continues in various forms to date, provides rebates to replace or retrofit older and more polluting diesel school buses. The use of school buses with newer technologies is intended to reduce the exposure of students and other people living in the community to air pollution with the intent of improving student health and educational performance. Funding is awarded to applicants based on a lottery system. The investigators used the random allocation of funding for applications submitted to school districts in the continental United States between 2012 and 2017 to assess whether this program improved student health and educational performance and community air quality, all at the school district level.

What This Study Adds

- This accountability study evaluated a program for replacing old diesel school buses with new, lower-emitting buses across the United States.
- The investigators compared student educational performance, school attendance, and respiratory emergency department visits among children in school districts that were selected for funding via a lottery mechanism with those in districts that were not selected for funding.
- Student educational performance and school attendance improved in districts that were selected for funding to replace old buses and improved the most in districts that replaced the oldest (pre-1990) diesel-powered school buses. There was no clear effect on emergency department visits.
- Community-level fine particle air pollution concentrations improved in school districts that had been selected for funding with the largest gains in districts that replaced the oldest buses, although it was not clear to what extent those improvements were driven by the new school buses.
- As electric school buses and other lower-emitting technologies become more widely available, additional benefits from continuing efforts to replace older school buses are expected and should be assessed.

APPROACH

Adar and colleagues evaluated the effects of the school bus replacement program by comparing school districts that were randomly selected in a lottery to those that entered the lottery but were not randomly selected (see **Statement Figure**). To see whether being selected for funding affected student health (based on school attendance and respiratory emergency department visits) or student performance (based on standardized tests of math and reading, writing, and related skills [hereafter referred to as *reading*]), the investigators compared these outcomes during the school year in which the school district entered the lottery to the following school year, when new school buses were expected to be in use.

To make the comparisons, the investigators collected information on lottery application details via a Freedom of Information Act request to the United States Environmental Protection Agency. They collected information on absenteeism and other school district characteristics from federal and state departments of education and on math and reading standardized test scores for children in grades 3–8 from a harmonized national dataset. They also obtained data on respiratory emergency department

This Statement, prepared by the Health Effects Institute, summarizes a research project funded by HEI and conducted by Dr. Sara D. Adar at the University of Michigan School of Public Health and her colleagues. Research Report 221 contains the detailed Investigators' Report and a Commentary on the study prepared by the HEI Review Committee.

visits of school-aged children from low-income (i.e., Medicaid) health insurance records and on fine particulate air pollution for each school year from a publicly available dataset from air quality modeling.

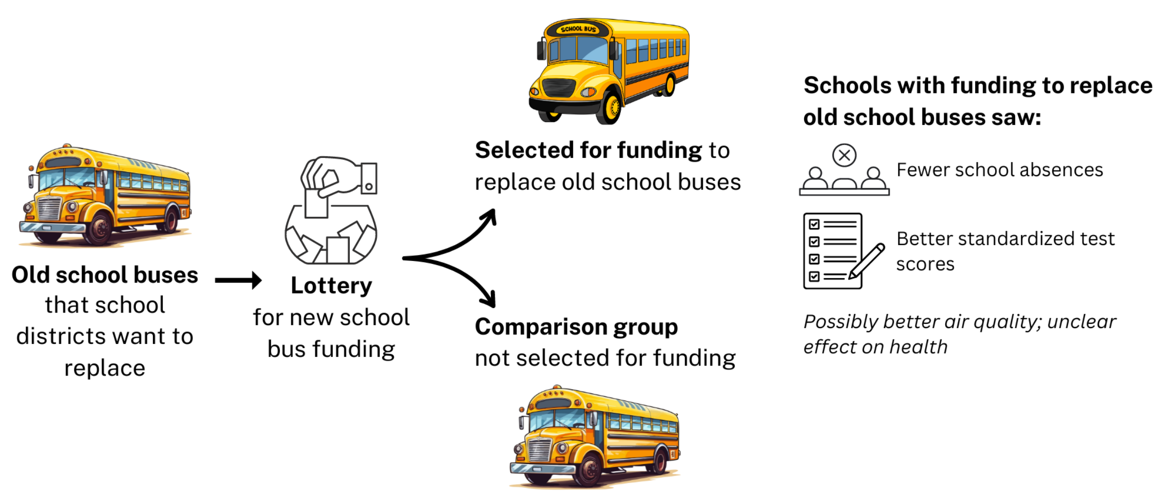
In their comparisons, Adar and colleagues accounted for student educational performance and health prior to the lottery, the region of the country in which the school district was located, and other school district characteristics. They tested the robustness of their results in many ways. For example, they compared results for school districts based on the ages of the school buses slated for replacement because larger gains would be expected the older the age (and therefore the higher the emissions) of the school bus being replaced.

KEY RESULTS

Adar and colleagues included 406 school districts that were selected for funding and 2,613 school districts that were not selected for funding in their analyses. School districts that were selected for funding had similar size, student demographics, and family incomes to those that were not selected for funding. Compliance with the intervention was high; 91% of school districts that were selected for funding documented the purchase of new school buses and scrappage of old school buses to receive the funding. Not all selected school districts had information available on what type of new school buses they purchased (if any), but in most cases where such information was available, old diesel school buses were replaced with new, less polluting diesel school buses. Few school districts that were selected for funding reported purchasing school buses that ran on other fuels, only one school district reported retrofitting a bus with emissions control technologies, and no school districts reported purchasing an electric school bus. No information was available on whether school districts that were not selected for funding also purchased new school buses or retrofit their existing school buses.

Adar and colleagues reported that in the year after the lottery, student test scores and school attendance improved the most in school districts that replaced the oldest (pre-1990) diesel school buses with newer school buses. There was also some indication of standardized test score and school attendance improvements in school districts where school buses slated for replacement were 1990s model years. The investigators indicated that the size of the effects on school attendance and test scores was comparable to those of typical interventions to reduce class size. They estimated that replacing pre-2000 model year buses through the program resulted in about 350,000 additional student-days of school attendance, presumed to be because of improved health, that otherwise would have been absences.

There was also a decrease in community-level, outdoor fine particle concentrations (i.e., a 1-$\mu g/m^3$ reduction) observed in the year after the lottery in districts where pre-1990 school buses were replaced. The magnitude of this decrease surprised the investigators because typical total outdoor fine particle concentrations in the United States are about 8 $\mu g/m^3$ and there are many other sources of air pollution. They could not identify any alternative explanations for these findings because the results did not change when they analyzed the data in different ways, for example, by looking at the change in outdoor fine particle concentrations instead of the concentrations themselves. They also showed that the outdoor fine particle concentration results did not change when accounting for potential differences or changes in school district characteristics or missing and excluded applications. Changes in emergency department visits for respiratory outcomes between communities selected for funding and not selected for funding were inconsistent and did not appear to be related to whether the school districts were selected for funding.



Statement Figure. Overview of the study by Adar and colleagues to assess a policy that provided funding to replace old school buses via a lottery mechanism. (Adapted from Investigators' Report Figure 1.)

HEI REVIEW COMMITTEE EVALUATION AND CONCLUSIONS

In its independent evaluation of the study, the Review Committee appreciated that Dr. Adar and colleagues brought together disparate datasets to conduct a novel and useful accountability study of a program to allocate funding for the replacement of old diesel school buses. Specifically, the Committee liked the approach to comparing school districts based on whether they were randomly selected for funding assuming they had replaced the school buses that they intended to replace, similar to how patients are randomly assigned treatments and the data are analyzed in trials of new medications. They agreed with the investigators that being selected for funding appeared to improve student educational performance and school attendance, especially when the intent was to replace pre-1990 school buses, and that the results for emergency department visits were less clear. The magnitude of the observed effect of being selected for funding on community-level, outdoor air pollution was larger than the Committee and the investigators expected, but the results were robust to sensitivity analyses (see above) and an alternative explanation could not be found. It was not clear how changing out a relatively small number of school buses could affect air quality in a school district so much. The Committee thought that the main results for school attendance and standardized test scores were well supported by the evidence.

In summary, selection for funding to replace or retrofit old school buses as part of the United States Environmental Protection Agency's program appears to have improved school attendance and standardized test scores, with the largest benefits for the replacement of the oldest (i.e., pre-1990) diesel school buses. The effects on emergency department visits for school-aged children and air quality are less clear and need further research. Results of the current study provide evidence of benefits of funding for school bus replacement programs by federal and state agencies. Additional focus on disadvantaged school districts and the adoption of new technologies like electric buses are also expected to reduce emissions from some of the oldest and highest emitting school buses. Therefore, it would be valuable to update the analyses in the future to evaluate the effects of programs to replace more of the older diesel school buses with newer and lower-emitting technologies. This work will be important to support the health and educational performance of schoolchildren and communities.

INVESTIGATORS' REPORT

Assessing the National Health, Education, and Air Quality Benefits of the United States Environmental Protection Agency's School Bus Rebate Program: A Randomized Controlled Trial Design

Sara D. Adar[1], Meredith Pedde[1], Richard Hirth[2], and Adam Szpiro[3]

[1]Department of Epidemiology, University of Michigan School of Public Health; [2]Department of Health Management and Policy, University of Michigan School of Public Health; [3]Department of Biostatistics, University of Washington School of Public Health

ABSTRACT

Introduction Approximately 25 million children ride buses to school in the United States. While school buses remain the safest school transport from a traffic accident perspective, older buses can expose students to high levels of diesel exhaust. These exposures can adversely affect health, which might cause missed school days and reduced learning. To hasten the transition to cleaner, lower-emission vehicles, the US Environmental Protection Agency's (US EPA*) ongoing School Bus Rebate Program randomly allocated over $27 million to replace older, higher-emission school buses with cleaner, lower-emission alternatives between 2012 and 2017. Here, we evaluated the effectiveness of this national program.

Methods Leveraging the randomized allocation of rebate funding, we assessed the impacts of the US EPA's 2012–2017 School Bus Rebate Programs on attendance, educational achievement, emergency department (ED) visits for respiratory causes among children in Medicaid, and community air pollution levels. We analyzed all districts linked to applications with complete data using modified intention-to-treat (ITT) modeling for randomized controlled trials, comparing changes in school-district levels of each outcome, after versus before each lottery year, by funding selection status. We also examined the heterogeneity of effects by model years of the replaced buses and by quartiles of estimated ridership on applicant buses.

Results Of the 3,019 applications that met our inclusion criteria, 406 were randomly selected for funding. The districts that were linked to these applications were similar in terms of size, demographic makeup, funding requests, and socioeconomic status to the districts linked to applications that were not selected for funding. The districts that were linked to applications selected for funding that replaced the oldest buses had improvements in attendance, educational performance, and ambient particulate matter ≤2.5 µm aerodynamic diameter ($PM_{2.5}$) concentrations in the year after the lottery, compared with districts linked to applications that were not selected for funding. Districts that replaced pre-1990 model year buses had the largest gains, with 0.45 percentage points (pp) and 95% confidence interval (CI) of 0.26 to 0.65 higher attendance (equivalent to 45 additional students attending school each day in an average-size school district of 10,000 students), 0.06 standard deviation (SD) higher reading and language arts (RLA) (95% CI: 0.05 to 0.07), 0.03 SD higher math test scores (0.01 to 0.04), and −1.0 µg/m^3 (−1.5 to −0.5) lower ambient $PM_{2.5}$ concentrations compared with districts not selected for funding. The replacement of model year 2000 and newer buses showed almost no effect on these outcomes. Districts replacing the oldest buses had suggestively higher ED visit rates, but these findings were not statistically distinguishable from no association and were sensitive to differing model specifications.

Based on the attendance improvements observed alone, we estimate that the total investment of $27 million by the US EPA for the 2012–2017 lotteries may have resulted in $350 million of benefits per year, although these benefits could not be distinguished from no benefit. Further investment of funds to replace all school buses manufactured before the year 1990 could lead to an additional $400 million of economic benefits per year and replacing all school buses manufactured before the year 2000 could lead to an additional $1.3 billion of economic benefits per year.

Conclusions We conclude that the US EPA's School Bus Rebate Program investments to remove very old buses from the fleets have positively affected communities.

This Investigators' Report is one part of Health Effects Institute Research Report 221, which also includes a Commentary by the Review Committee and an HEI Statement about the research project. Correspondence concerning the Investigators' Report may be addressed to Dr. Sara D. Adar, Professor of Epidemiology, University of Michigan School of Public Health, 1415 Washington Heights, Ann Arbor, Michigan 48109-2029; email: *sadar@umich.edu*. Dr. Adar is a member of the HEI Review Committee and has been recused from all discussions of the report.

Although this document was produced with partial funding by the United States Environmental Protection Agency under Assistance Award CR–83998101 to the Health Effects Institute, it has not been subjected to the Agency's peer and administrative review and may not necessarily reflect the views of the Agency, and no official endorsement by it should be inferred. The contents of this document also have not been reviewed by private party institutions, including those that support the Health Effects Institute; therefore, it may not reflect the views or policies of these parties, and no endorsement by them should be inferred.

* A list of abbreviations and other terms appears at the end of this volume.

INTRODUCTION

Approximately 25 million children ride buses to school each day in the United States.[1] Although school buses remain the safest means to transport children to school from a traffic accident perspective,[2] the use of older school buses often means children can experience high exposure to diesel exhaust during their commutes.[3-5] With exposures to pollutants inside school buses reaching levels as high as 10 times the levels found in ambient air,[3-5] even relatively short commutes on highly polluting school buses can contribute a disproportionately high fraction to students' daily air pollution exposures.[6] This is of great concern given that exposures to diesel exhaust and other traffic-related pollutants can adversely affect health,[7] increase school absenteeism,[8,9] and have been associated with lower educational performance.[10-13]

Diesel exhaust can enter school buses indirectly via leaky cabins or directly through open windows or doors.[3-5,14,15] Importantly, however, not all school buses have the same emissions or generate the same exposures to diesel exhaust. For example, the US EPA reports that diesel PM filters reduce PM emissions from buses by 60% to 90%.[16] Our testing of in-cabin air during nearly 600 trips on 200 Seattle school buses showed that clean air technologies can result in up to 50% reductions in particle concentrations inside bus cabins.[17] These reductions in onboard air pollution levels came from the use of diesel oxidation catalysts that reduce toxic emissions from the tailpipe as well as closed crankcase ventilation systems that minimize emissions from the engine block. Similar testing of school buses in Alabama and Colorado found similar pollution reductions with the same technologies.[18,19] While this work suggests that school districts should retrofit older buses with these technologies or replace them with newer buses that incorporate these technologies, retrofits cost nearly $10,000 per bus.[20] New buses are even more expensive, at approximately $100,000 to $300,000 per bus.[21] As a result, the average school bus is on the road for 16 years before being decommissioned, and millions of children ride older, highly polluting buses.[22-24]

To help hasten the transition of school districts to cleaner, lower emission vehicles, the US EPA set aside funding to help public and private fleet owners replace or retrofit old, highly polluting school buses under the National Clean Diesel Rebate Program, which was authorized by the Diesel Emissions Reduction Act (DERA) of 2010.[25] Using a random lottery approach to allocate funds, the US EPA awarded over $27 million to replace or retrofit school buses between the program's start in 2012 and 2017, and the program continues to distribute funds.[25-32] Despite this large investment and the opportunity for investigation under a classical causal framework, the effectiveness of this rebate program on the health or educational performance of students or community air quality levels had yet to be evaluated. In addition, general research into the effects of school bus clean air technologies on health is scarce.

In this study, we took advantage of the randomized allocation of funding for school bus replacements and retrofits to causally assess the national effects of the US EPA School Bus Rebate Program on student health, educational achievement, and community air quality levels. We used school attendance and ED visits for respiratory causes as our measures of health based on a large literature of exposures to ambient air pollution.[33] Previous research has demonstrated relationships between cleaner, lower emission school buses, and higher attendance rates[34] in the Puget Sound[17] area and Georgia.[35] Another study documented fewer ED visits by children for bronchitis, asthma, pneumonia, and pleurisy among Washington State school districts that retrofitted their school buses compared with those that did not.[36] In addition to markers of health, we chose to study the educational effects of the US EPA School Bus Rebate Program because earlier observational work found that school bus retrofits led to improvements in test scores in Georgia[35] and nationwide,[37] and the general educational literature has repeatedly demonstrated higher educational achievement with better attendance rates.[38-40] Lastly, we evaluated community air quality levels to determine whether there were additional benefits of this US EPA program to populations beyond the school bus riders.

SPECIFIC AIMS

Our study included three project aims:

1. To quantify the health impacts of the US EPA's School Bus Rebate Program funding to replace older, higher emission school buses with newer, lower emission buses as assessed by student attendance rates for all students and ED visit rates for respiratory causes in school-aged Medicaid beneficiaries (5–18 years old) using a randomized controlled trial design.

   Hypothesis 1a: School districts linked to applications selected for funding in a random lottery will see greater improvements in student attendance rates after their school bus replacements or retrofits compared with school districts linked to applications that were not selected for funding for school bus replacements or retrofits.

   Hypothesis 1b: School districts linked to applications selected for funding in a random lottery will see greater reductions in ED visits for respiratory causes among school-aged Medicaid beneficiaries (5–18 years old) after their school bus replacements or retrofits compared with school districts linked to applications that were not selected for funding for school bus replacements or retrofits.

2. To assess the educational impacts of the US EPA School Bus Rebate Program funding to replace older, higher emission, school buses with newer, lower emission buses, as assessed by educational achievement scores using a randomized controlled trial design.

Hypothesis 2: School districts linked to applications selected for funding through a random lottery will see greater improvements in educational achievement scores after receiving funding for school bus replacements or retrofits than school districts linked to applications that were not selected for funding for school bus replacements or retrofits.

3. To examine the ambient air quality impacts of the US EPA School Bus Rebate Program funding to replace older, higher emission, school buses with newer, lower emission buses, as assessed by average $PM_{2.5}$ concentrations using a randomized controlled trial design.

   Hypothesis 3: School districts linked to applications selected for funding through a random lottery will see greater reductions in ambient $PM_{2.5}$ concentrations in their communities after receiving funding for school bus replacements or retrofits than school districts linked to applications that were not selected for funding for school bus replacements or retrofits.

STUDY DESIGN AND METHODS

US EPA SCHOOL BUS REBATE PROGRAM

Starting in 2012, the US EPA's School Bus Rebate Program provided funding to replace diesel-powered school buses that had older engines with new diesel, alternate fuel, battery, hybrid, or electric school buses (**Table 1** and Table A1 in Appendix A; available on the HEI website).[25-29] From 2015 through 2017, funding was also permitted for retrofits of school buses with diesel oxidation catalysts and crankcase ventilation systems.[27-29] In 2016 and 2017, additional funding was made available for US EPA-verified, fuel-operated heaters onboard buses to reduce idling for heat.[28,29] While no funding was awarded for school bus replacements or retrofits in 2013, for brevity we refer to 2012–2017 as our analysis years throughout.

The US EPA's eligibility criteria allowed school districts and private bus transportation companies that serviced school districts (herein referred to as "entrants") to apply for funding for up to 5 or 10 buses, depending on program year. Entrants could submit up to two applications for a school district and year depending on fleet size and program year. No restrictions were placed on the number of years that an entrant could enter the lottery. Bus transportation companies were also permitted to enter the lottery more than once if they were requesting funding for buses that serviced different school districts.*

There were also specific age requirements for the engines eligible to be replaced in each funding cycle and for the type and age of eligible replacement engines (see Table 1 and Appendix Table A1 for details).

The deadline for each of the rebate programs was the end of the calendar year, at which point the US EPA randomly selected applications to be funded using a random number generator until all available funds were exhausted. Because some US EPA regional offices had additional funding for school bus replacements, these offices awarded funding to additional applications based on the randomized rank of applications that did not receive funding from the US EPA national program (Appendix Table A2).

The US EPA notified all entrants at the end of the school year if their application was selected for funding. Selected entrants then purchased their replacement buses or installed retrofits in the summer following the lottery and used their new buses for the first time at the start of the next school year. For example, all 2012 entrants who had an application selected for funding in the lottery replaced their buses in the summer of 2013 and began using the new buses at the start

*Although the US EPA Clean School Bus Program documents state that applicants could only submit one application in 2012 and 2014, the data indicate that some applicants did submit two applications in these years.

Table 1. Summary of the US EPA School Bus Rebate Program, by Year

Lottery Year	Diesel Bus Engines to be Replaced	Replacement Bus Engines	Number of Applications Allowed	Number of Buses Eligible per Application	Rebate Amount per Bus	Number of Selected Applications	Number of Unselected Applications	Total Funding Awarded (millions)
2012	1994–2003	2012 or later	1	5	\$20K–\$30K	36	973	\$1.88
2014	≤ 2006	2014 or later	1	5	\$15K–\$25K	73	474	\$3.94
2015	≤ 2006	2015 or later	1 (if fleet ≤100 buses) 2 (if fleet >100 buses)	10	\$15K–\$25K	86	451	\$6.04
2016	≤ 2006	2016 or later	1 (if fleet ≤100 buses) 2 (if fleet >100 buses)	10	\$15K–\$25K	92	422	\$7.24
2017	≤ 2006	2017 or later	1 (if fleet ≤100 buses) 2 (if fleet >100 buses)	10	\$15K–\$20K	143	403	\$8.20
					Total	**430**	**2,723**	**\$27.29**

of the 2013–2014 school year, which we refer to throughout this analysis as the *after* lottery year. For 2012 entrants, the 2012–2013 school year would then be the *before* lottery year. All entrants with applications selected for funding were required to submit proof of new bus purchases and of scrappage of their old buses. If these entrants failed to do so then the funding would not be awarded by the US EPA even though the entrant was selected for funding.

STUDY DESIGN

As shown in **Figure 1**, the core hypothesis that this project tested was whether or not school districts served by entrants with applications that were randomly selected for funding to replace older school buses with newer, lower emission buses under the US EPA's School Bus Rebate Program had greater improvements between the year before and the year after the lottery in (1) attendance, (2) respiratory-related ED visit rates for school-aged children on Medicaid, (3) educational achievement, and (4) air quality as compared to districts served by entrants with applications not selected to receive funding. Because selection in the lottery is random, there should be no systematic bias by known or unknown characteristics related to districts served by entrants with and without replacements. Similarly, because we use outcome measures from administrative datasets that are collected independently of school bus allocations, there should be no bias in ascertainment by lottery status. As such, this randomized controlled trial design and our evaluation of districts served by entrants with randomly selected applications rather than districts served by entrants with bus purchases should provide strong evidence of causal relationships between our health, educational, and air quality metrics.

DATA

US EPA School Bus Rebate Program Applications

We obtained data on all 3,153 applications for the 2012–2017 lotteries from the US EPA under a Freedom of Information Act request. The data for all applications included the lottery selection status, school district served (when an entrant was a private bus transportation company that serviced a school district), number of buses requested to be replaced or retrofitted, and funding requested. Henceforth we use the term 'district' to refer to either the school district that submitted the application or the school district served by the bus transportation company that submitted the application.*

For districts with applications that were ultimately awarded funding, we also received information on the engine model years of the replaced buses, although this information was most often averaged across all replaced buses in the district (Appendix Figure A1). Information about the age of the buses was not available for districts with applications not selected for funding.

*Multiple applications could be linked to the same school district if more than one bus transportation company serving a district entered the lottery.

For all aims, we restricted our sample to applications from entrants that serviced school districts in the continental United States that could be matched with individual school districts because school districts were our unit of analysis. While there were applications from entrants that serviced Hawaii that we would have liked to include, all of the Hawaiian Islands are part of a single school district, so we could not disentangle any units affected by bus replacements. Similarly, we excluded private bus transportation companies and school district consortium applicants that represented multiple school districts. For Aims 1 and 2, we further excluded applications from entrants without attendance and educational performance reporting requirements (i.e., private schools, nontraditional schools [e.g., special education and technology centers], and tribal schools).

School District Descriptive Data

To assess the balance of characteristics between entrants with selected and unselected applications to the US EPA's School Bus Rebate Program as well as to compare the school districts serviced by entrants to the US EPA School Bus Rebate Programs to all US school districts, we obtained school district information from the US Department of Education's yearly Local Education Agency (School District) Universe Survey Data. These publicly available data include the number of students (total and by grade and by race and ethnicity), number of schools, and urbanicity (i.e., city, suburb, town, rural) of each district. The land area of each school district was provided in the National Center for Education Statistics School District Geographic Relationship files for the school years of 2013–2014, 2015–2016, and 2017–2018. As a proxy for district socioeconomic status, we used data on the number of students in a school who were eligible for the free and reduced-price lunch program during the baseline school year from the US Department of Education's yearly Public Elementary/Secondary School Universe Survey Data, which we aggregated to the district level.

Attendance Data

For Hypothesis 1a, we collected 2012–2013 through 2018–2019 school year annual attendance rates for school districts served by entrants that submitted funding applications from each state's Department of Education, either from public websites or through individual data requests with a state. Annual attendance rates reflect the average number of students present at all schools in a district across all days of a school year divided by the number of students serviced by that district. We focused on annual attendance rate data for both the school year before and after the purchase of new buses to have the most proximate data to an entrant's lottery selection status and to reduce the influence of trends. In cases where the attendance counts were averaged across a school year but the number of students serviced by a district was collected on a single day, it was possible for the attendance rate to exceed 100 percent. As our modeling approach quantifies the change

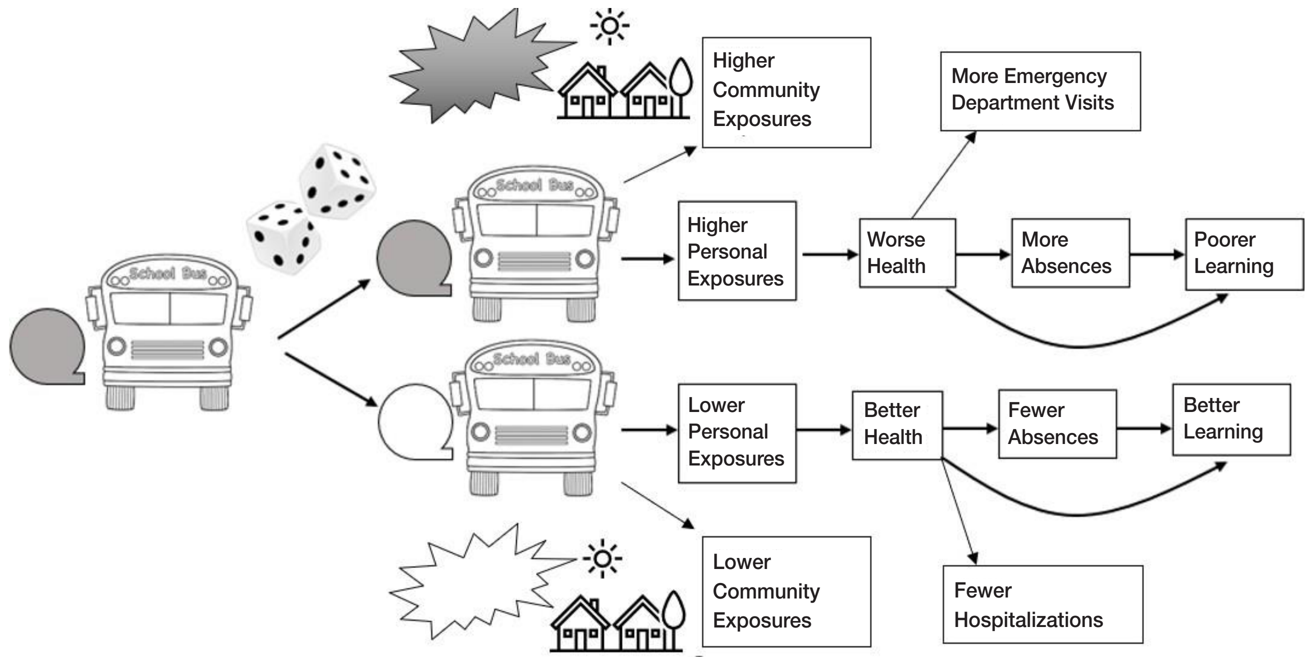


Figure 1. Conceptual framework of the study. Buses with gray plumes represent school buses with higher levels of emissions. Buses with white plumes represent school buses with lower emissions. The dice represent the mechanism by which the EPA Clean School Bus Program allots funds: a random number generator. Houses with a gray plume represent a neighborhood exposed to higher levels of school bus emissions. Houses with a white plume represent a neighborhood exposed to lower levels of school bus emissions.

in attendance rates in terms of percentage points, we elected to retain the few absolute attendance rates greater than 100 percent. To ensure that we were using the highest quality data, we did void any changes in attendance rates of 5 pp or more between the before and after lottery school years. This cutoff was consistent with the literature as an indicator of unreasonable levels and seemed to be consistent with errors in our review of the data.[17,41-42]

Respiratory-Related Emergency Department Visit Data

We obtained claims and enrollee data from the Research Data Assistance Center (ResDAC, a Centers for Medicare and Medicaid Services contractor) for all ED visits from respiratory causes among school-aged children in Medicaid to inform Hypothesis 1b. We restricted our study population to children who were at least 5 years old and no older than 18 years old on September 1 of the school year of interest, had full Medicaid eligibility throughout the school year (i.e., September 1 to May 31), and whose home zip code intersected one of the school districts served by the US EPA Clean School Bus Program entrants. Although we gathered data from the Children's Health Insurance Program (CHIP), we did not ultimately use these records because states do not use consistent unique identifiers across years for CHIP children. This prevented us from being able to link CHIP participant records across time, which was needed to create a complete record of the participant's health and eligibility throughout a school year because the data span two calendar years.

To define the total population of interest (i.e., the denominator of our ED visit rate) and identify any ED visits, we used the Medicaid Analytic Extract (MAX) Personal Summary, Inpatient, and Outpatient files (for years 2012–2015) and Transformed Statistical Medicaid Information System (T-MSIS) Analytic (TAF) Demographic and Eligibility, Inpatient, and Outpatient files (for years 2014–2019). Two sources of data were required because the Centers for Medicare & Medicaid Services (CMS) transitioned to a new data system during the years of our study period. The two data systems overlapped for two calendar years because states transitioned to the new system at different times throughout that period. The differences between the two data systems are largely unrelated to the data elements we use in this work.[43] We then used the revenue, place of service, type of service, and procedure codes to identify claims originating from visits to the ED during the periods that children are typically in school (i.e., September 1 to May 31). Our outcome was defined by ED visits during the school year with a primary diagnosis of asthma (International Classification of Diseases [ICD]-9 code: 493; ICD-10 code: J4520, J4522, J4521, J449, J440, J441, J45990, J45991, J45909, J45998, J45902, J45901), upper respiratory infection (ICD-9 code: 460–466, 477; ICD-10 code: J00, J0100, J0110, J0120, J0130, J0140, J0190, J029, J0390, J040, J050, J0410, J0411, J042, J050, J0510, J0511, J0430, J0431, J060, J069, J209, J210, J218, J301, J305, J3081, J302, J3089, J300, J309), or pneumonia (ICD-9 code: 480–486; ICD-10 code: J120, J121, J122, J1281, J1289, J129, J13, J181, J150, J151, J14, J154, J153, J1520, J15211, J15212, J1529, J158, J155, J156, A481, J159, J157, J160, J168, B250, A3791, A221, B440, J17, J180, J189). Children did not need to have filed claims to be included in the enrollee file. Because the Medicaid data were aggregated at the level of zip code rather than school district, we calculated spatially weighted averages from all zip codes that intersected a school district. We felt that this approach, which is similar to that of Beatty and Shimshack,[36] was reasonable given that across the nation over 60% of zip codes are nearly entirely contained (>90% by area) within a single school district.

Education Data

For Hypothesis 2, we obtained normalized school-district test-score data for math and RLA for the 2012–2013 through 2017–2018 school years from the Stanford Education Data Archive 4.1 (SEDA).[44] Data were not yet available for the 2018–2019 school year at the completion of this project. These data are derived from state-level testing data for children in grades 3 through 8, which is collected under federal mandate as a result of the Elementary and Secondary Education Act and the former No Child Left Behind Act.[45] Because these Acts allow for states to select or design a test of their choice that measures student achievement relative to the state's proficiency standards, student testing data are not directly comparable across location and time. To account for differences in testing between states and across time, experts at the Stanford Center for Educational Policy Analysis have generated normalized educational performance metrics from test results submitted to the US Education Department's EDFacts data system by district, grade, and subject.[45] These data are the only publicly available educational metrics for all US school districts at the school-district level that are comparable across the nation. To best reflect all children that may ride the buses, we averaged SEDA data across grades, by district and year.

Air Quality Data

To evaluate Hypothesis 3, we mapped each school district served by an entrant to modeled ambient $PM_{2.5}$ from September 1 to May 31, predicted at a $0.01^o \times 0.01^o$ spatial resolution[46], and averaged across all grid cells that intersected the school-district boundaries. The $PM_{2.5}$ estimates were predicted globally at a monthly scale using measures of aerosol optical depth from satellites. Briefly, the researchers used the GEOS-Chem chemical transport model, which incorporates physics, chemistry, and atmospheric transport, to determine the relationship between aerosol optical depth and $PM_{2.5}$ and to generate geophysical estimates of $PM_{2.5}$. The researchers then used monitored levels of $PM_{2.5}$ and a geographically weighted regression to improve their $PM_{2.5}$ predictions. The model performed well within North America with monthly coefficient of determination and root-mean-square error values ranging from 0.51 to 0.68 and 2.0 to 3.1 µg/m³, respectively.[46]

STATISTICAL METHODS AND DATA ANALYSIS

Assessing Balance Between Selected and Unselected Lottery Applications

We first compared means (using independent two-sample *t-tests*) and proportions (using Pearson chi-squared test) of baseline measured characteristics of the districts served by entrants with selected and unselected applications in each analytical dataset (i.e., attendance, ED visits, education, and air quality) to check for balance among the applications by selection status. The baseline year was the *before* year for each application, which is described earlier.

Quantifying Differences Between Selected and Unselected Lottery Applications

To evaluate the effect of the US EPA's School Bus Rebate Program on each of our outcomes of interest, we analyzed data for all applications linked to districts with complete data using modified ITT analyses to leverage the benefits of the random assignment of funding. Our analysis was considered as a modified one because we, by necessity, had to restrict our analyses to only those school districts with complete data on the outcomes of interest. In our models, we evaluate the effect of being selected for funds in the lottery on the outcome in the year after the lottery adjusted for the outcome in the year before the lottery prior to when the new buses were in use. This accounts for any time-invariant differences that occurred by chance between districts served by entrants with selected and unselected applications. It also supports causal conclusions with the greatest efficiency by focusing on within-area differences between the pre- and post-randomization levels.[47,48]

Our primary analyses for Hypotheses 1a (attendance), 2 (educational achievement), and 3 (ambient $PM_{2.5}$ concentration) outcomes used the following linear regression model (**Equation 1**):

$$\begin{aligned} Y_{it+1} = {} & \beta_0 + \beta_1 Selected_{it} \\ & + \beta_2 Y_{it} \\ & + \beta_3 RepeatedDistrict_{it} \\ & + \beta Region_i \\ & + \beta Time_{it} \\ & + \epsilon_{it} \end{aligned} \tag{1}$$

To evaluate the effects of the School Bus Rebate Program on rates of ED visits among school-aged children (Hypothesis 1b), we used the following Poisson regression model (**Equation 2**):

$$\begin{aligned} \log E(Y_{it} + 1) = {} & \beta_0 + \beta_1 Selected_{it} \\ & + \beta_2 \left(\frac{Y_{it}}{Population_{it}}\right) \\ & + \beta_3 RepeatedDistrict_{it} \\ & + \beta Region_i \\ & + \beta Time_{it} \\ & + \log Population_{it+1} \\ & + \epsilon_{it} \end{aligned} \tag{2}$$

In both models, Y_{it+1} is the continuous outcome for each application's school district *i* in the school year after the year *t* lottery (i.e., 2012, or 2014–2017 lotteries), at which time the new buses were in use. We adjusted for Y_{it}, which is the outcome for school district *i* in the school year of lottery *t* prior to when the new buses were in use. $Selected_{it}$ is an indicator equal to 1 if an application's school district i was selected to receive funding in lottery year t and 0 if not. Therefore, β_1 is the model outcome of interest as it reflects the ITT effect of being selected for funding.

Because the later lottery years allowed entrants with large fleets to submit up to two applications and districts could be represented more than once by different bus transportation companies, we adjusted all models for districts with more than one application within a lottery year using the binary indicator $RepeatedDistrict_{it}$. Similarly, because some US EPA regions provided additional funding for the purchase of new, lower emission buses, applications from entrants serving districts from regions with added funding had an increased likelihood of being selected in the lottery. Therefore, we included fixed effects for the US EPA regions ($Region_i$). To maximize power, we included data from all lottery years in our model but included fixed effects for the lottery year ($Time_{it}$) to adjust for any potential confounding over time that may have occurred because the percentages of applications selected in the lottery changed by year. In our models for the ED visit rate (2), we further adjusted for *Population*, which captures the total number of 5- to 18-year-old Medicaid beneficiaries in an application's school district i in the school year before and after the lottery. Although there will inherently be some correlation between our adjustment variables, collinearity between covariates is not a concern because we are not interpreting the coefficients for any covariate except the exposure of interest. Importantly, these terms were included in our models to get an unbiased (i.e., unconfounded) estimate of being selected for funding on our outcomes of interest.

Because entrants are not limited to entering the lottery in only 1 year, we estimated associations and 95% CIs using general estimating equations (GEE). We fit these models using robust standard errors clustered at the state level to account for any potential correlation in the data. Clustering at the state level in the GEE framework accounts for all correlations across smaller units of aggregation, such as within school districts.[73] This is the case because the assumption required for the validity of GEE is independence between clusters, and virtually any correlation structure within clusters is acceptable. We fit our models with an independent working correlation structure for computational efficiency. Although GEE is robust to the selection of the covariance matrix, we also tested exchangeable and autocorrelation structures in sensitivity analyses to ensure the robustness of our findings.

Effect Modification

Given that older buses were subject to more lenient emission standards[57], we evaluated the heterogeneity of the effects of replacing a bus on our outcomes by age of the replaced buses. To do so, we used Equations 3 and 4, which replaced the $Selected_{it}$ indicator in models (1) and (2), respectively, with three indicator variables for selected applications that replaced pre-1990, 1990–1999, or 2000 and newer model year buses ($Pre\text{-}1990_{it}$, $1990\text{–}1999_{it}$, and $2000plus_{it}$, respectively). The reference group for this analysis was therefore the unselected applications. We used this approach because we only had average bus age information on the buses requested to be replaced from selected applications and not on the buses represented from applications that were not selected for funding.

$$\begin{aligned} Y_{it+1} = {} & \beta_0 + \beta_1 Pre\text{-}1990_{it} \\ & + \beta_2 1990\text{–}1999_{it} \\ & + \beta_3 2000plus_{it} \\ & + \beta_4 Y_{it} \\ & + \beta_5 RepeatedDistrict_{it} \\ & + \beta Region_i + \beta Time_{it} \\ & + \epsilon_{it} \end{aligned} \tag{3}$$

$$\begin{aligned} \log E(Y_{it+1}) = {} & \beta_0 + \beta_1 Pre\text{-}1990_{it} \\ & + \beta_2 1990\text{–}1999_{it} \\ & + \beta_3 2000plus_{it} \\ & + \beta_4 \left(\frac{Y_{it}}{Population_{it}}\right) \\ & + \beta_5 RepeatedDistrict_{it} \\ & + \beta Region_i \\ & + \beta Time_{it} \\ & + \log Population_{it+1} \\ & + \epsilon_{it} \end{aligned} \tag{4}$$

We also considered if our results were influenced by the number of buses replaced in a district served by an entrant. As an ecological analysis, we were inherently unable to isolate the effects of the intervention on school bus riders. Although school bus emissions may affect nonriders when buses idle near where students play, study, or wait for other transportation,[49-51] aggregating data at the school-district level will likely dilute the true association for bus riders, especially when the district is large relative to the number of buses replaced. Therefore, we evaluated effect modification of our main associations in Hypotheses 1a, 1b, and 2 by quartiles of the fraction of children who are likely to ride the buses requested for replacement (i.e., those most directly affected by the treatment) ($EstimatedRidershipQuart_{it}$) using **Equation 5** for Hypotheses 1a and 2 and **Equation 6** for Hypothesis 1b. With no databases of school bus ridership rates at the district level, we estimated this fraction by multiplying the number of buses requested for replacement by 72 (the capacity for a standard school bus) and dividing by the total student enrollment for a district at baseline. For Hypotheses 3, we examined quartiles of the number of buses requested for replacement as the effect modifier ($NumBusesReq_{it}$) to see if entrants that applied to replace more buses saw stronger improvements in air quality (**Equation 7**).

$$
\begin{aligned}
Y_{it+1} = \beta_0 + \beta_1 Selected_{it} \\
&+ \beta_2 EstimatedRidershipQuart_{it} \\
&+ \beta_3 Selected_{it} \times EstimatedRidershipQuart_{it} \\
&+ \beta_4 Y_{it} \\
&+ \beta_5 RepeatedDistrict_{it} \\
&+ \beta Region_{i} \\
&+ \beta Time_{it} \\
&+ \epsilon_{it}
\end{aligned}
\tag{5}
$$

$$
\begin{aligned}
\log E(Y_{it+1}) = \beta_0 + \beta_1 Selected_{it} \\
&+ \beta_2 EstimatedRidershipQuart_{it} \\
&+ \beta_3 Selected_{it} \times EstimatedRidershipQuart_{\mathrm{it}} \\
&+ \beta_4 \left(\frac{Y_{it}}{Population_{it}}\right) \\
&+ \beta_5 RepeatedDistrict_{it} \\
&+ \beta Region_{i} \\
&+ \beta Time_{it} \\
&+ \log Population_{it+1} \\
&+ \epsilon_{it}
\end{aligned}
\tag{6}
$$

$$
\begin{aligned}
Y_{it+1} = \beta_0 + \beta_1 Selected_{it} \\
&+ \beta_2 NumBusesReqQuart_{it} \\
&+ \beta_3 Selected_{it} \times NumBusesReqQuart_{it} \\
&+ \beta_4 Y_{it} \\
&+ \beta_5 RepeatedDistrict_{it} \\
&+ \beta Region_{i} + \beta Time_{it} \\
&+ \epsilon_{it}
\end{aligned}
\tag{7}
$$

Secondary Analyses

We explored effect modification by the fraction of children on free and reduced-price lunches as an indicator of potentially sensitive populations and by urbanicity because students in rural districts are likely to ride the school bus for more than 30 minutes in each direction.[52] We also looked at effect modification by the number of schools and number of students in a district to see whether results were stronger in smaller districts, where a larger fraction of students may have the potential to be affected by the bus emissions. We also evaluated effect modification of our findings by race and, for Hypothesis 1b, we also tested for effect modification of this association by the fraction of children enrolled in Medicaid by district.

To study all the effect modifiers mentioned, we used interaction terms between the effect modifier of interest and the main effect of being selected in the lottery.

Mediation Analysis Based on our conceptual model outlined in Figure 1, we examined whether (1) respiratory ED visits mediated associations between school bus upgrades and attendance, and (2) increased attendance rates mediated the observed associations between school bus upgrades and educational achievement. To do so, we used the methodologies of VanderWeele.[53] Specifically, in the first mediation analysis we examined the direct effects of changes in buses on attendance as well as the indirect effects through ED visits. In the second mediation analysis, we examined the direct effects of changes in buses on educational achievement as well as the indirect effects through school attendance.

Burden Estimations To understand the full benefit of the US EPA's School Bus Rebate Program, we estimated the nationwide effects on student attendance by multiplying the total number of US students in districts served by entrants with selected applications at baseline by the observed primary effect estimate **(Table 2)** and by the number of days in the school year (i.e., 180). We further quantified the potential national effects of replacing only the oldest buses by using the US EPA's Age Distribution Tool for MOVES2014 to estimate what fraction of the US school bus fleet was pre-1990 and, separately, 1990–1999 in calendar year 2021.[23,24] We then applied these fractions to the total count of all US students at the midpoint of our analysis period (i.e., 50,115,178 children in the school year 2015–2016[54]) to estimate the attendance benefits based on the observed effect sizes for buses of those model years.

We estimated the economic benefits of the US EPA's School Bus Rebate Program using values from the US EPA on the unit value of a lost day of school. The US EPA has derived this estimate from the economic literature for its Benefits Mapping and Analysis Program (BenMAP),[55] a tool to calculate the economic benefits of environmental regulations. The US EPA estimates the value of a lost day of school at a fixed value of $1,000 for all of the nation, which incorporates aspects of caregiver costs for elementary school children and the loss of learning for middle and high school students. Caregiver costs are estimated as the average wage income an adult caregiver would have earned had they not stayed home with the absent child. The loss of learning value is estimated as the effect of a single school absence on learning, measured by end-of-course test scores. That estimate is then multiplied by estimates of the effect of learning on adult income.

We also evaluated how representative the districts served by entrants who submitted applications to the US EPA lottery were to all US school districts by comparing means (using independent two-sample *t-tests*) and proportions (using Pearson chi-squared test) of baseline measured characteristics for the US EPA entrant districts (i.e., the *before* year for each entrant) to all US school districts (we used data from the 2015–2016 school year for the US school districts as it was the midpoint of the study period).

Sensitivity Analyses

For Hypothesis 1b (ED visits), our primary analysis spatially weighted the Medicaid data from all zip codes contained within a school district served by an entrant, which may make it more difficult to detect any true association (i.e., introduce bias toward the null) by including additional areas

Table 2. Effects of School Bus Replacements on Attendance, Respiratory ED Visits, Educational Performance, and Ambient $PM_{2.5}$ Concentrations for All Replaced Buses, by Model Year Replaced, and by Fraction of Ridership on Replaced Buses

	Attendance (pp)		ED Visits (% change)		Education: RLA (SD)		Education: Math (SD)		$PM_{2.5}$ (μg/m³)	
Model	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**
Overall effect of replacement	0.06[a]	–0.01, 0.13	3.5[b]	–2.3, 9.7	0.005[c]	–0.008, 0.017	–0.001[d]	–0.011, 0.010	–0.04[e]	–0.11, 0.04
Effect of replacement for different model years of replaced buses[f]										
pre-1990	0.45	0.26, 0.65	4.9	–5.0, 15.8	0.062	0.050, 0.074	0.025	0.011, 0.039	–0.95	–1.45, –0.45
1990-1999	0.10	–0.03, 0.23	–8.8	–21.1, 5.5	–0.003	–0.020, 0.014	–0.012	–0.032, 0.009	–0.04	–0.15, 0.08
2000 and newer	–0.03	–0.16, 0.09	9.2	0.8, 18.2	0.003	–0.011, 0.018	0.001	–0.014, 0.016	–0.01	–0.08, 0.06
Effect of replacement by ridership on buses requested for replacement[g,h,i]										
Quartile 1:	–0.01	–0.15, 0.14	4.1	–2.5, 11.1	0.013	–0.004, 0.029	0.005	–0.011, 0.022	0.08	–0.05, 0.22
Quartile 2:	0.05	–0.05, 0.16	3.4	–9.8, 18.6	0.005	–0.017, 0.027	0.012	–0.010, 0.033	–0.09	–0.19, 0.02
Quartile 3:	0.05	–0.10, 0.19	1.8	–23.8, 35.9	–0.024	–0.049, 0.001	–0.019	–0.044, 0.007	–0.11	–0.27, 0.05
Quartile 4:	0.14	–0.05, 0.32	–4.1	–17.1, 10.9	0.024	–0.010, 0.057	0.001	–0.028, 0.030	–0.05	–0.19, 0.09
	P value: 0.69		*P* value: 0.77		*P* value: 0.13		*P* value: 0.38		*P* value: 0.22	

[a] Dependent variable is the attendance in the year after the lottery. Model is adjusted for the attendance in the year before the lottery, US EPA Region, lottery year, and an indicator for having more than one application in a given lottery year.

[b] Dependent variable is the number of respiratory-related ED visits among 5- to 18-year-old Medicaid beneficiaries in the year after the lottery. Model is adjusted for the ED visit rate for respiratory causes in the year before the lottery, US EPA Region, lottery year, and an indicator for having more than one application in a given lottery year.

[c] Dependent variable is the RLA standardized test score in the year after the lottery. Model is adjusted for the RLA standardized test score in the year before the lottery, US EPA Region, lottery year, and an indicator for having more than one application in a given lottery year.

[d] Dependent variable is the math standardized test score in the year after the lottery. Model is adjusted for the math standardized test score in the year before the lottery, US EPA Region, lottery year, and an indicator for having more than one application in a given lottery year.

[e] Dependent variable is the $PM_{2.5}$ in the year after the lottery. Model is adjusted for the $PM_{2.5}$ in the year before the lottery, US EPA Region, lottery year, and an indicator for having more than one application in a given lottery year.

[f] Independent variables of interest are indicator variables for winners replacing buses with average model year pre-1990, 1990–1999, and 2000 and newer. Model is adjusted for US EPA Region, lottery year, and an indicator for having more than one application in a given lottery year.

[g] Quartile thresholds for ridership for the attendance and ED Visits analyses are: Q1: 0.05–3.8%; Q2: 3.8–8.1%; Q3: 8.1–16.2%; Q4: 16.2–100%. Quartile thresholds for ridership for the Education analyses are: Q1: 0.14–3.6%; Q2: 3.6–8.0%; Q3: 8.0–15.5%; Q4: 15.5–100%.

[h] For the $PM_{2.5}$ analysis, the effect modifier of interest is the number of buses requested for replacement. Quartile thresholds are: Q1: 1 bus; Q2: 2–3 buses; Q3: 4–5 buses; Q4: 6–20 buses.

[i] *P* values are for interaction term.

that may not be affected by the school buses. To test the sensitivity of our results to this choice, we restricted our models to only include children from zip codes that were entirely contained within a school district's boundary. Similarly, our primary analysis was restricted to ED visits during the school year to target the times that children were most at risk for an event due to bus exposures.

We used several techniques to further evaluate whether the exclusion of applications post-randomization may have unexpectedly distorted our randomization. First, we investigated whether the exclusion was related to the selection status. Next, we assigned a range of outcomes (i.e., changes in attendance, educational performance, ED visits, and $PM_{2.5}$ levels *before* to *after* the lottery) for all excluded applications (n = 134). These assigned values capture the full range of changes in our data and therefore reflect extreme scenarios for the missing information. We then reran our models with these extreme outcome values for the districts served by the entrants from excluded applications to generate upper and lower bounds for our estimates. Finally, we reran all models after using multiple imputation with Rubin's rules for missing outcome variables so we could understand the potential effects on the results of conducting a complete case analysis.[56]

To ensure that our findings were robust to our analytic choices, we tested the sensitivity of our primary results for Hypotheses 1a, 2, and 3 to alternatively modeling the difference in outcomes before and after the lottery rather than controlling for the prior year's level. We also tested the sensitivity of including further adjustment for free and reduced-price lunch eligibility as well as for adjusting for the baseline levels of the other outcomes (e.g., we adjusted for baseline RLA, math, $PM_{2.5}$, and attendance levels in the respiratory ED visit analysis). We further adjusted our primary model for differences in the number of schools, number of students, percentage of students who are white, and the percentage of students eligible for free and reduced-price lunch between the *before* and *after* years to account for any differences in time trends across districts.

RESULTS

Across all five lottery years, there were a total of 3,153 applications to the US EPA School Bus Rebate Program (**Figure 2**). Of these 3,153 overall and 430 selected applications, 3,019 (96%) represented school districts that met our inclusion criteria for the full study, 406 of which were randomly selected for funding. Compliance with the intervention was very high, with 91% of these 406 applicants receiving the funds and thus providing proof of purchase of a new school bus and scrappage of the old school bus. Information on the school bus purchasing behaviors was not available for school districts that were selected for funding but did not receive the funding or for the school districts that were not selected for funding. Districts served by entrants that submitted applications that were included in our analysis were larger in terms of the number of students and schools, had a higher proportion of students that were white, had a lower proportion of students eligible for the free and reduced-price lunch program, and were less urban than all US school districts (**Table 3**). Within the US EPA School Bus Rebate Program, districts served by entrants with selected applications were statistically similar to those that were not selected for funding with respect to their size, demographic makeup, urbanicity, funding and number of buses requested, a proxy for socioeconomic status (i.e., free and reduced-price lunch eligibility), attendance rates, and educational performance at baseline. ED visits (0.048 vs. 0.053 visits/child school year) and $PM_{2.5}$ concentrations (6.9 vs. 7.2 μg/m^3) were slightly lower in the districts linked to selected applications compared with the districts linked to unselected applications (**Table 4**). Importantly, we found that lottery status was not predictive of missingness for any of the outcomes considered (Appendix Table A5). Further details for each outcome are presented separately later.

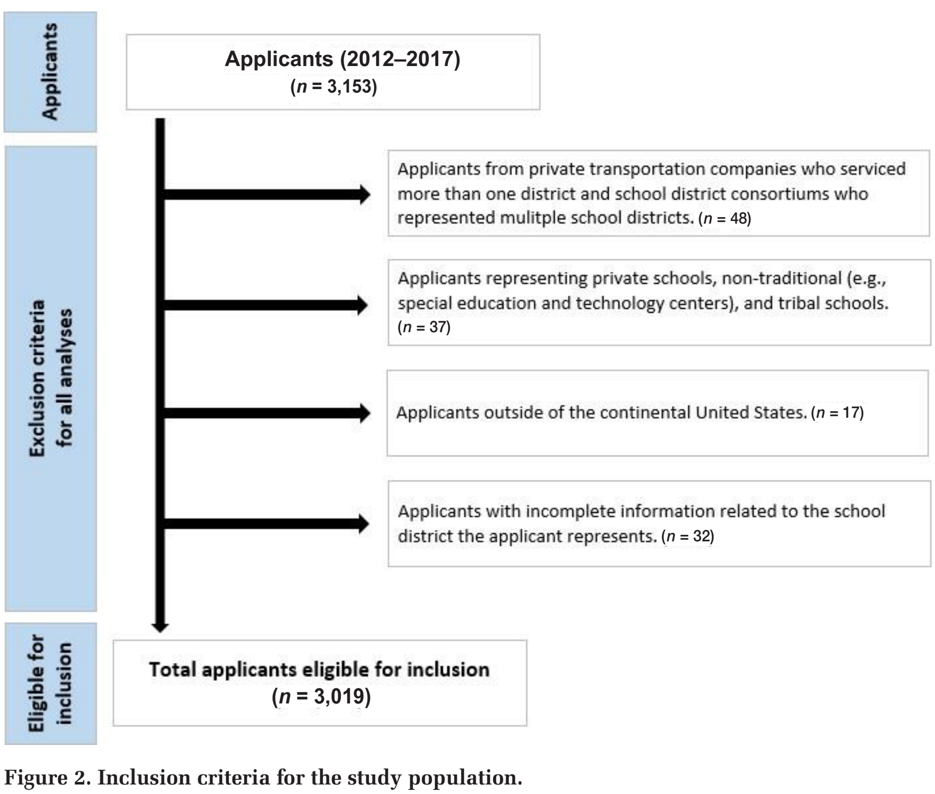


Figure 2. Inclusion criteria for the study population.

Table 3. Comparison of US EPA School Bus Rebate Program Participants[a] to all US School Districts[b]

Characteristic	Included DERA Applications n = 3,019 Mean (SD)	Included DERA Applications Percent Missing	All US School Districts N = 18,893 Mean (SD)	All US School Districts Percent Missing	P value
Schools in district	15 (38)	0	6 (19)	1.6	<0.0001
Students in district	9,134 (27,504)	0.2	2,969 (11,351)	9.4	<0.0001
District students, White (%)	72.5 (25.6)	0.2	64.0 (31.9)	11.4	<0.0001
District students eligible for free lunch (%)	40.3 (20.5)	1.8	44.3 (24.5)	19.8	<0.0001
District students eligible for reduced-price lunch (%)	7.8 (4.5)	6.3	8.2 (6.5)	29.8	0.0001
District land area (square miles)	275 (646)	0.8	279 (1,379)	30.3	0.84
District urbanicity, n (%)		0		0.2	<0.0001
Rural	1,276 (42.3)		8,283 (44.0)		
Town	648 (21.5)		3,131 (16.6)		
Suburb	798 (26.4)		4,212 (22.4)		
City	297 (9.8)		3,221 (17.1)		

DERA = Diesel Emissions Reduction Act; SD = standard deviation

[a] Characteristics for the districts linked to the US EPA School Bus Rebate Program applications represent the time of baseline, which is the school year before the new buses were (or would have been, in the case of unselected applications) purchased and therefore differs by which year(s) an application was entered in the lottery.

[b] Characteristics for the US school districts represent the 2015–2016 school year. The districts linked to DERA applications are included in this set of all US School Districts.

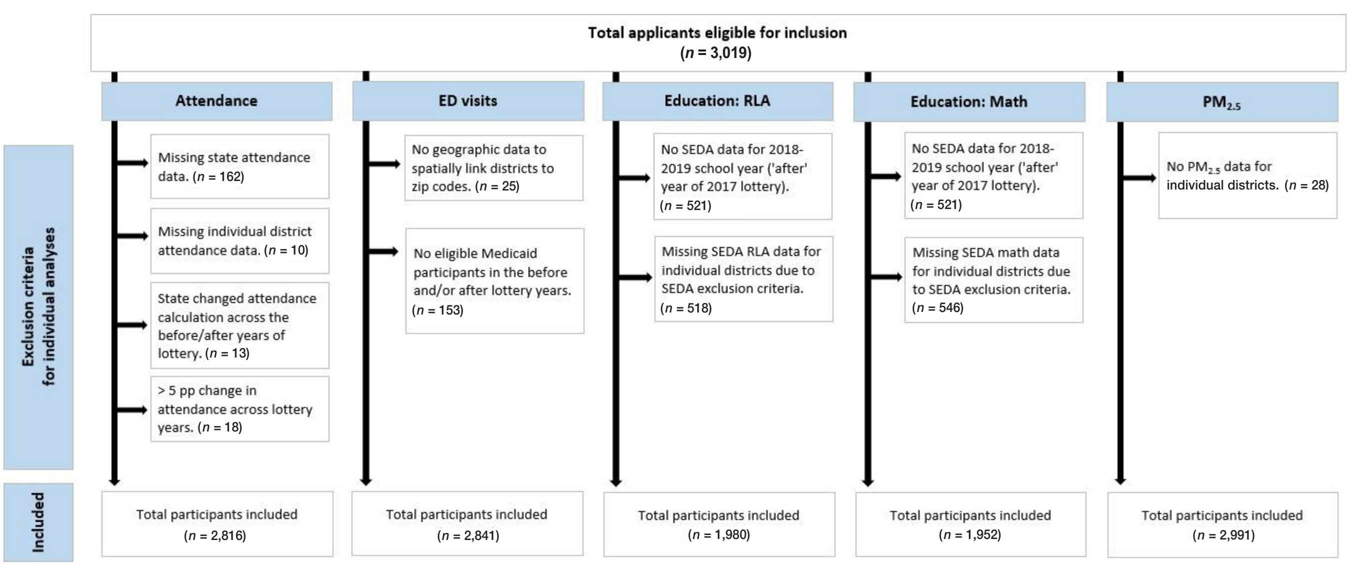


Figure 3. Missingness for each outcome of interest.

Table 4. Baseline Characteristics of School District Entrants by Lottery Status[a]

Characteristic	Unselected Applications	Selected Applications	*P* value
All applications eligible for inclusion	*n* = 2,613	*n* = 406	
Schools in district, *n*; mean (SD)	15 (40)	13 (30)	0.34
Students in district, *n*; mean (SD)	9,245 (28,198)	8,422 (22,559)	0.51
District students – White, %; mean (SD)	72.5 (25.7)	72.8 (24.7)	0.80
District students eligible for free lunch, %; mean (SD)	40.4 (20.6)	39.5 (19.7)	0.37
District students eligible for reduced-price lunch, %; mean (SD)	7.8 (4.4)	8.0 (5.1)	0.59
Buses requested for replacement/retrofit, *n*; mean (SD)	3.6 (2.7)	3.7 (3.1)	0.81
Funding requested for replacement/retrofit, $; mean (SD)	78,483 (58,574)	73,660 (62,121)	0.13
District land area, square miles; mean (SD)	279 (672)	250 (443)	0.25
District urbanicity; *n* (%)			
Rural	1,094 (41.9)	182 (44.8)	0.44
Town	571 (21.9)	77 (19.0)	
Suburb	687 (26.3)	111 (27.3)	
City	261 (10.0)	36 (8.9)	
Attendance analysis cohort	*n* = 2,433	*n* = 383	
District attendance rate, %; mean (SD)	94.90 (1.38)	94.75 (1.39)	0.06
ED visit analysis cohort	*n* = 2,459	*n* = 382	
District ED visit rate among 5–18-year-olds on Medicaid, visits/child school-year; mean (SD)	0.053 (0.057)	0.048 (0.034)	0.02
Education: RLA analysis cohort	*n* = 1,766	*n* = 214	
District average RLA standardized test score, SD; mean (SD)	0.068 (0.292)	0.064 (0.306)	0.87
Education: math analysis cohort	*n* = 1,743	*n* = 209	
District average math standardized test score, SD; mean (SD)	0.058 (0.338)	0.040 (0.352)	0.47
$PM_{2.5}$ analysis cohort	*n* = 2,590	*n* = 401	
District average $PM_{2.5}$, µg/m^3; mean (SD)	7.15 (1.49)	6.92 (1.30)	0.002

[a] Baseline is the school year before the new buses were (or would have been, in the case of unselected applications) purchased and therefore differs by which year(s) an application was entered in the lottery.

ATTENDANCE

District-level attendance data were not available for applications linked to districts in Pennsylvania (n = 66) for any years; Alabama (n = 18), Arizona (n = 10), and Montana (n = 11) for the 2015–2016 through 2018–2019 school years; New Jersey (n = 43) for 2012–2013 and 2013–2014; and North Dakota (n = 14) for 2012–2013. An additional n = 10 application observations were excluded from the analysis due to missing attendance data for some individual districts or to methodological changes in the reporting of the attendance data across the *before* and *after* school years (n = 13). Ultimately, we were able to evaluate associations using attendance data from 2,816 (93%) of the eligible US EPA applications (**Figure 3**), of which 383 were selected for funding (Table 4).

Nationwide, we found that districts linked to applications selected for the School Bus Rebate funding had suggestively, although not statistically different, higher attendance rates in the year after the lottery compared with districts linked to applications not selected for funding (0.06 pp; 95% CI: –0.01 to 0.13) (Table 2). Funding had the largest effects for districts that replaced older buses. For example, districts replacing a pre-1990 model year bus had the largest improvements in attendance at 0.45 pp (0.26 to 0.65), translating to 45 additional students attending school each day in an average size district of 10,000 students. Districts that replaced 1990–1999 model year buses had a 0.10 pp improvement in attendance (–0.03 to 0.23) whereas there was little improvement for districts that replaced model year 2000 and newer buses (–0.03 pp; –0.16 to 0.09). The estimates of the effects of being selected in the lottery were similarly larger for districts with higher levels of estimated ridership on the buses requested for replacement, with estimates reaching as high as 0.14 pp (–0.05 to 0.32) for the highest estimated ridership group, translating to 14 additional students attending school each day in an average size district of 10,000 students, although these results could not be distinguished from no association. While present in the expected dose–response fashion, these groups could not be statistically distinguished from one another. There was no evidence of effect modification by urbanicity or levels of free lunch eligibility, but there was some indication of stronger effects among districts with fewer schools and students (**Table 5**). The results were robust across multiple alternative specifications of our model in sensitivity analyses, including using the change in attendance rate as the dependent variable and adjusting for covariates such as free and reduced-price lunch eligibility, changes in district characteristics *after* compared with *before* the lottery, and for other outcomes at baseline (**Table 6**). Although the overall results were weakened after using multiple imputation to address missing data, the model year results remained robust across all analyses. The results were also robust to our evaluations of potential selection bias (Appendix Table A4).

Based on our main results, we estimated that the upgrade of older buses through the US EPA's School Bus Rebate Funding Programs between 2012 and 2017 resulted in 351,093 additional student days of attendance per year (95% CI: –70,678 to 772,865). Notably, this is likely an underestimate of the total effect because it does not incorporate any sustained effects of the funding over time. Furthermore, extrapolation of our data suggests that funding to replace all pre-2000 model year buses in school districts nationwide could lead to 1.3 million additional student days of attendance each year (95% CI: 247,443 to 2,406,511); approximately 400,000 from the replacement of pre-1990 buses (408,729; 95% CI: 232,103 to 585,446) and approximately 900,000 from the replacement of 1990s model year buses (918,311; 95% CI: –236,343 to 2,072,964).*

*Confidence intervals for the replacement of all pre-2000 model-year buses do not equal the sum of the lower and upper confidence intervals for the pre-1990 and 1990s model-year bus estimates because confidence intervals are not additive.

RESPIRATORY-RELATED EMERGENCY DEPARTMENT VISITS

As shown in Figure 3, we were able to evaluate associations using ED visit rate data from n = 2,841 (94%) of the eligible US EPA applications after excluding 25 applications linked to school districts with missing school-district geographies (which was needed to link zip codes to school districts) and 153 applications linked to districts without child-aged Medicaid enrollees in either the *before* or *after* year of the lotteries. Of these applications, 382 were selected for funding (Table 4).

Counter to our hypothesis, we found that school bus replacements were associated with an overall increase in ED visit rates for respiratory causes among 5- to 18-year-old Medicaid enrollees, although these associations were imprecise and generally could not be statistically distinguished from no association (Table 2). Notably, however, there was no logical dose–response relationship observed by replaced model year (Table 2), and the results were sensitive to different modeling strategies and our evaluations of potential selection bias (**Table 7**, Appendix Table A4). For example, the overall results using imputed data to account for missingness suggested a reduction in ED visits among districts linked to applications selected for funding as compared to districts linked to applications not selected for funding, although the estimate was imprecise (–11.3%; 95% CI: –29.0% to 10.8%).

In our secondary analyses, we found little evidence that ED visits mediated the relationship between being selected for the US EPA school bus upgrade funding and attendance rates (–7.4%; 95% CI: –3,207% to 4%) (**Table 8**).

EDUCATIONAL PERFORMANCE

The SEDA data had a larger fraction of missing information compared with the other outcomes partially because data for the 2018–2019 school year were unavailable at the time of authoring this report. In addition, SEDA excludes test scores due to incomplete student participation (<95% in a subject for a given grade in a given year), state reporting to EDFacts, or differences in test administration within state-subject-grade-year, which can happen if districts were allowed to administer locally selected assessments (see Table 4 in Fahle et al. for a

Table 5. Effect Modification Results for the Effects of School Bus Replacements on Attendance, Respiratory ED Visits, Educational Performance, and Ambient $PM_{2.5}$ Concentrations[a,b]

	Attendance (pp)		ED Visits (% change)		Education: RLA (SD)		Education: Math (SD)		$PM_{2.5}$ (μg/m³)	
Model	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**
Overall effect of replacement	0.06	−0.01, 0.13	3.5	−2.3, 9.7	0.005	−0.008, 0.017	−0.001	−0.011, 0.010	−0.04	−0.11, 0.04
Effect of replacement by urbanicity										
Rural	0.02	−0.10, 0.14	7.3	−5.9, 22.4	−0.006	−0.028, 0.016	−0.014	−0.032, 0.005	−0.004	−0.08, 0.08
Town	0.14	−0.01, 0.28	−8.8	−26.6, 13.3	0.001	−0.021, 0.022	0.015	−0.017, 0.047	0.02	−0.12, 0.16
Suburb	0.07	−0.09, 0.23	2.6	−4.8, 10.5	0.025	0.007, 0.044	0.011	−0.009, 0.031	−0.11	−0.25, 0.03
City	0.01	−0.38, 0.40	9.1	−11.5, 34.5	−0.003	−0.025, 0.018	−0.008	−0.034, 0.018	−0.06	−0.23, 0.12
	P value: 0.61		*P* value: 0.30		*P* value: 0.22		*P* value: 0.26		*P* value: 0.41	
Effect of replacement by district free lunch eligibility										
Low eligibility	0.09	−0.02, 0.20	4.7	−7.4, 18.3	0.008	−0.009, 0.025	0.009	−0.002, 0.020	0.03	−0.07, 0.13
High eligibility	0.01	−0.08, 0.11	3.4	−3.1, 10.2	0.0003	−0.018, 0.018	−0.009	−0.025, 0.006	−0.11	−0.21, −0.002
	P value: 0.35		*P* value: 0.84		*P* value: 0.49		*P* value: 0.07		*P* value: 0.09	
Effect of replacement by number of schools in a district										
Low number of schools	0.11	0.01, 0.21	−2.3	−12.6, 9.2	0.001	−0.018, 0.020	-0.005	−0.020, 0.011	0.04	−0.06, 0.13
High number of schools	−0.005	−0.09, 0.08	4.1	−1.9, 10.6	0.008	−0.006, 0.022	0.003	−0.009, 0.015	−0.12	−0.24, 0.002
	P value: 0.08		*P* value: 0.33		*P* value: 0.54		*P* value: 0.44		*P* value: 0.06	
Effect of replacement by number of students in a district										
Low number of students	0.10	0.004, 0.19	−4.5	−14.9, 7.3	-0.002	−0.021, 0.018	−0.004	−0.021, 0.013	0.03	−0.06, 0.11
High number of students	0.01	−0.07, 0.10	4.3	−1.8, 10.7	0.010	−0.003, 0.023	0.002	−0.009, 0.014	−0.10	−0.22, 0.01
	P value: 0.12		*P* value: 0.21		*P* value: 0.28		*P* value: 0.56		*P* value: 0.08	
Effect of replacement by fraction of district students who are White										
Low percentage White students	0.06	−0.05, 0.16	3.6	−2.8, 10.3	0.013	−0.001, 0.027	0.003	−0.011, 0.016	−0.09	−0.20, 0.01
High percentage White students	0.07	−0.02, 0.16	2.8	−8.4, 15.3	−0.004	−0.026, 0.017	−0.004	−0.022, 0.014	0.02	−0.07, 0.11
	P value: 0.83		*P* value: 0.91		*P* value: 0.19		*P* value: 0.59		*P* value: 0.12	
Effect of replacement by fraction of children on Medicaid										
Low Medicaid eligibility			−3.5	−19.9, 16.4						
High Medicaid eligibility			3.9	−2.0, 10.0						
			P value: 0.47							

[a] For the attendance, education, and $PM_{2.5}$ analyses, the dependent variable is the outcome in the year after the lottery. Models are adjusted for the outcome in the year before the lottery, US EPA Region, lottery year, and an indicator for having more than one application in a given lottery year. For the ED visit analysis, the dependent variable is the number of respiratory-related ED visits among 5- to 18-year-old Medicaid beneficiaries in the year after the lottery. Model is adjusted for the ED visit rate for respiratory causes in the year before the lottery, US EPA Region, lottery year, and an indicator for having more than one application in a given lottery year.

[b] *P* values are for interaction term.

Table 6. Effects of School Bus Replacements on Attendance in Secondary and Sensitivity Analyses

	Primary Model[a]		Change in Outcome[b]		Adjusted for Free and Reduced-Price Lunch Eligibility[c]		Adjusted for Changes in School District Characteristics[d]		Adjusted for Baseline levels of Other Outcome Measures[e]	
Model	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**
Overall effect of replacement	0.06	–0.01, 0.13	0.08	–0.01, 0.17	0.07	–0.01, 0.14	0.07	0.00, 0.15	0.03	–0.04, 0.11
Effect of replacement for different model years of replaced buses[g]										
pre-1990	0.45	0.26, 0.65	0.41	0.17, 0.66	0.44	0.17, 0.71	0.42	0.20, 0.64	0.48	0.12, 0.83
1990–1999	0.10	–0.03, 0.23	0.14	–0.01, 0.28	0.14	0.06, 0.23	0.15	0.06, 0.24	0.01	–0.11, 0.13
2000 and newer	–0.03	–0.16, 0.09	–0.02	–0.17, 0.12	–0.03	–0.15, 0.10	–0.03	–0.15, 0.09	–0.09	–0.25, 0.06
Number of observations	2,816		2,816		2,650		2,608		1,966	

	Multiple Imputation[f]	
Model	**Parameter Estimate**	**95% CI**
Overall effect of replacement	0.02	–0.07, 0.12
Effect of replacement for different model years of replaced buses[g]		
pre-1990	0.47	0.05, 0.90
1990–1999	0.09	–0.05, 0.24
2000 and newer	–0.02	–0.14, 0.11
Number of observations	3,010	

[a] Dependent variable is the attendance in the year after the lottery. Model is adjusted for the attendance in the year before the lottery, US EPA Region, lottery year, and an indicator for having more than one application in a given lottery year.

[b] Dependent variable is the difference in the attendance rate in the years before and after the lottery. Model is adjusted for US EPA Region, lottery year, and an indicator for having more than one application in a given lottery year.

[c] Primary model, additionally adjusted for district free and reduced-price lunch eligibility rates.

[d] Primary model, additionally adjusted for the difference in the district number of schools, number of students, percentage of students that are White, and the free and reduced-price lunch eligibility rates in the years before and after the lottery.

[e] Primary model, additionally adjusted for baseline levels of district average $PM_{2.5}$, RLA and math standardized scores, and respiratory-related ED visit rates among 5- to 18-year-old Medicaid beneficiaries.

[f] Primary model including observations with previously missing outcome measures newly estimated with multiple imputation methods.

[g] Independent variables of interest are indicator variables for selected districts replacing buses with average model year pre-1990, 1990–1999, and 2000 and newer.

Table 7. Effects of School Bus Replacements on Respiratory ED Visits in Secondary and Sensitivity Analyses

	Primary Model[a]		Adjusted for Free and Reduced-Price Lunch Eligibility[b]		Adjusted for Changes in School District Characteristics[c]		Adjusted for Baseline Levels of Other Outcome Measures[d]		Only Within Districts Fully Within School District Boundaries[e]	
Model	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**
Overall effect of replacement	3.5	−2.3, 9.7	3.5	−2.5, 9.9	1.7	−4.7, 8.6	8.5	2.0, 15.5	7.2	−8.6, 25.8
Effect of replacement for different model years of replaced buses[g]										
pre-1990	4.9	−5.0, 15.8	1.6	−8.1, 12.3	1.5	−8.3, 12.5	9.8	0.0, 20.5	5.1	−11.1, 24.3
1990–1999	−8.8	−21.1, 5.5	−10.7	−23.9, 4.8	−12.6	−26.3, 3.8	−2.5	−17.5, 15.2	−10.6	−30.1, 14.4
2000 and newer	9.2	0.8, 18.2	10.1	0.8, 20.4	8.1	−1.7, 18.8	13.1	2.2, 25.1	12.2	−10.4, 40.4
Number of observations	2,841		2,669		2,625		1,970		870	

	Multiple Imputation[f]	
Model	**Parameter Estimate**	**95% CI**
Overall effect of replacement	−11.3	−29.0, 10.8
Effect of replacement for different model years of replaced buses[g]		
pre-1990	4.2	−11.7, 22.9
1990–1999	−12.7	-−27.4, 5.0
2000 and newer	3.9	−21.9, 38.2
Number of observations	3,019	

[a] Dependent variable is the number of respiratory-related ED visits among 5- to 18-year-old Medicaid beneficiaries in the year after the lottery. Model is adjusted for the ED visit rate for respiratory causes in the year before the lottery, US EPA Region, lottery year, and an indicator for having more than one application in a given lottery year.

[b] Primary model, additionally adjusted for district free and reduced-price lunch eligibility rates.

[c] Primary model, additionally adjusted for the difference in the district number of schools, number of students, percentage of students that are White, and the free and reduced-price lunch eligibility rates in the years before and after the lottery.

[d] Primary model, additionally adjusted for baseline levels of district average $PM_{2.5}$, RLA and math standardized scores, and attendance.

[e] Model only includes districts that are completely contained within the boundary of a given school district.

[f] Primary model including observations with previously missing outcome measures newly estimated with multiple imputation methods.

[g] Independent variables of interest are indicator variables for selected districts replacing buses with average model year pre-1990, 1990–1999, and 2000 and newer.

Table 8. Results from Mediation Analyses of the Effect of the US EPA School Bus Rebate Program on Education and Attendance Outcomes

	Education: RLA (% change)		Education: Math (% change)		Attendance (pp)	
Model	**Parameter Estimate**[a]	**95% CI**[b]	**Parameter Estimate**[a]	**95% CI**[b]	**Parameter Estimate**[c]	**95% CI**[b]
Total effect	0.007	–0.007, 0.020	–0.001	–0.015, 0.013	0.05	–0.03, 0.12
Controlled direct effect	0.007	–0.007, 0.020	–0.001	–0.016, 0.012	0.05	–0.03, 0.12
Natural direct effect	0.007	–0.007, 0.020	–0.001	–0.016, 0.012	0.05	–0.03, 0.12
Natural indirect effect	0.0002	–0.0004, 0.002	0.0001	–0.001, 0.001	–0.004	–0.02, 0.002
Percentage mediated	2.7	–7.5, 222.4	–16.9	–3972.5, -2.4	–7.4	–3207.1, 4.0

[a] The dependent variable is the standardized test score in the year after the lottery. The mediator is the attendance rate in the year after the lottery. Model is adjusted for the standardized test score in the year before the lottery, the attendance rate in the year before the lottery, US EPA Region, lottery year, and an indicator for having more than one application in a given lottery year.

[b] Bootstrap bias corrected 95% confidence limits.

[c] The dependent variable is the attendance rate in the year after the lottery. The mediator is the ED visit rate in the year after the lottery. Model is adjusted for the attendance rate in the year before the lottery, the ED visit rate in the year before the lottery, US EPA Region, lottery year, and an indicator for having more than one application in a given lottery year.

list of state/year/subject exclusions).[45] As a result, observations for $n = 518$ and $n = 546$ applications were dropped in our RLA and math analyses, respectively, leaving us with RLA data from 1,980 (66%) and math data from 1,952 (65%) of all eligible applications. Note that the portions of data relative to the 2012 and 2014–2016 lottery years when SEDA data were available were 79% and 78%, respectively (Figure 3). Among the school districts linked to applications in this analysis, 214 applications in the RLA analyses and 209 applications in the math analyses were selected for funding (Table 4).

When evaluating the effects of US EPA's School Bus Rebate Program funding, we found that districts linked to applications selected for funding had, on average, 0.005 SD higher average RLA test scores (95% CI: –0.008 to 0.017) and –0.001 SD lower average math test scores (–0.011 to 0.010) in the year after the lottery compared with districts linked to applications that were not selected for funding (Table 2). While these district-level results were small and not statistically distinguishable from the null, we observed large effects among districts that replaced the oldest buses. Specifically, districts replacing a pre-1990 model year bus had the largest improvements in RLA scores at 0.062 SD (0.050 to 0.074) and in math scores at 0.025 SD (0.011 to 0.039). For context, these results are equivalent in magnitude to average district income increasing by 10% and 4% for the RLA and math subjects, respectively.*

In contrast, there was little evidence of an improvement in RLA or math test scores for districts that replaced 1990–1999 (RLA: –0.003 SD; –0.020 to 0.014; math: –0.012 SD; –0.032 to 0.009) or 2000 and newer (RLA: 0.003 SD; –0.011 to 0.018; math: 0.001 SD; –0.014 to 0.016) model year buses. There was also suggestive evidence that the effects of lottery selection on RLA — but not math — scores were larger for districts with the highest levels of estimated ridership on the buses requested for replacement, with effects of 0.024 SD (–0.010 to 0.057), but this was not supported by a dose–response relationship across all ridership categories, and the ridership groups could not be statistically distinguished from one another. There was little evidence of effect modification by urbanicity, SES, or school-district size (Table 5).

Our primary results were robust to using the change in standardized test scores before and after the lottery as the dependent variable. They were also robust to adjustments for free and reduced-price lunch eligibility, changes in school-district characteristics compared with before the lottery, and baseline values of other outcomes. These results were also robust to the inclusion of districts linked to excluded applications, even with extreme assumed values of the outcome and inclusion of applications linked to districts with missing data through the use of multiple imputation (**Table 9,** Appendix Table A4). In our secondary analysis, we found little evidence that attendance mediated the relationship between US EPA school bus upgrade funding selection and educational performance. Specifically, we observed that only 2.7% (95% CI: –7.5% to 222%) of the total effect of the US EPA's clean bus funding on RLA test scores was mediated by attendance (Table 8). The result for math test scores was even less supportive of a mediative effect of attendance (–16.9%; –3,973% to –2.4%).

AIR QUALITY

We were able to link ambient $PM_{2.5}$ concentrations to 2,991 (99%) of all eligible US EPA applications (Figure 3). Of these, 401 applications were selected for funding (Table 4). After adjusting for baseline differences in $PM_{2.5}$, region, and lottery

*Results determined from replacing the lottery indicator with a measure of district average income from the SEDA dataset.

Table 9. Effects of School Bus Replacements on Educational Performance in Secondary and Sensitivity Analyses

Model	Primary Model[a]		Change in Outcome[b]		Adjusted for Free and Reduced-Price Lunch Eligibility[c]	
	Parameter Estimate	95% CI	Parameter Estimate	95% CI	Parameter Estimate	95% CI
RLA						
Overall effect of replacement	0.005	–0.008, 0.017	0.005	–0.008, 0.019	0.005	–0.009, 0.018
Effect of replacement for different model years of replaced buses[g]						
pre-1990	0.062	0.050, 0.074	0.068	0.055, 0.082	0.066	0.054, 0.078
1990–1999	–0.003	–0.020, 0.014	–0.003	–0.019, 0.013	–0.001	–0.018, 0.016
2000 and newer	0.003	–0.011, 0.018	0.003	–0.013, 0.019	0.003	–0.012, 0.019
Number of observations	1,980		1,980		1,883	
Math						
Overall effect of replacement	–0.001	–0.011, 0.010	–0.001	–0.012, 0.010	0.001	–0.010, 0.012
Effect of replacement for different model years of replaced buses[g]						
pre-1990	0.025	0.011, 0.039	0.028	0.013, 0.042	0.042	0.027, 0.058
1990–1999	–0.012	–0.032, 0.009	–0.013	–0.032, 0.007	–0.005	–0.025, 0.014
2000 and newer	0.001	–0.014, 0.016	0.001	–0.015, 0.016	–0.001	–0.017, 0.016
Number of observations	1,952		1,952		1,853	

Model	Adjusted for Changes in School District Characteristics		Adjusted for Baseline Levels of Other Outcome Measures[d]		Multiple Imputation	
	Parameter Estimate	95% CI	Parameter Estimate	95% CI	Parameter Estimate	95% CI
RLA						
Overall effect of replacement	0.004	–0.010, 0.018	0.006	–0.007, 0.019	0.001	–0.011, 0.013
Effect of replacement for different model years of replaced buses[g]						
pre-1990	0.066	0.054, 0.079	0.048	0.032, 0.063	0.057	0.006, 0.108
1990–1999	–0.005	–0.023, 0.013	–0.001	–0.017, 0.015	–0.003	–0.024, 0.017
2000 and newer	0.002	–0.014, 0.018	0.005	–0.011, 0.020	0.000	–0.015, 0.016
Number of observations	1,853		1,811		3,019	
Math						
Overall effect of replacement	–0.001	–0.012, 0.011	0.000	–0.011, 0.011	0.008	–0.006, 0.022
Effect of replacement for different model years of replaced buses[g]						
pre-1990	0.039	0.023, 0.054	0.022	0.008, 0.037	0.033	–0.022, 0.087
1990–1999	–0.010	–0.030, 0.011	–0.011	–0.031, 0.009	0.000	–0.021, 0.020
2000 and newer	–0.002	–0.020, 0.015	0.000	–0.015, 0.015	0.012	–0.005, 0.029
Number of observations	1,823		1,776		3,019	

[a] Dependent variable is the standardized test score in the year after the lottery. Model is adjusted for the standardized test score in the year before the lottery, US EPA Region, lottery year, and an indicator for having more than one application in a given lottery year.

[b] Dependent variable is the difference in the standardized test score in the years before and after the lottery. Model is adjusted for US EPA Region, lottery year, and an indicator for having more than one application in a given lottery year.

[c] Primary model, additionally adjusted for district free and reduced-priced lunch eligibility rates.

[d] Primary model, additionally adjusted for the difference in the district number of schools, number of students, percentage of students that are White, and the free and reduced-priced lunch eligibility rates in the years before and after the lottery.

[e] Primary model, additionally adjusted for baseline levels of district average $PM_{2.5}$, attendance rate, and respiratory-related ED visit rates among 5- to 18-year-old Medicaid beneficiaries.

[f] Primary model including observations with previously missing outcome measures newly estimated with multiple imputation methods.

[g] Independent variables of interest are indicator variables for selected districts replacing buses with average model year pre-1990, 1990–1999, and 2000 and newer.

year, we found that districts linked to applications selected for the School Bus Rebate funding had, on average, 0.04 μg/m^3 lower $PM_{2.5}$ levels (95% CI: –0.11 to 0.04) in the year after the lottery compared with districts linked to applications that were not selected for funding (Table 2). We also found larger $PM_{2.5}$ reductions among those districts replacing older buses and among districts that requested the most replacement buses, with evidence of clear dose responses for both, although these groups could not be statistically distinguished from one another. Reductions also appeared to be larger among districts with the highest fraction of students on reduced-price or free lunch (Table 5). Our results were largely robust to using the change in $PM_{2.5}$ concentration as the dependent variable as well as to adjustment for changes in district characteristics *after* compared with *before* the lottery and to differences between districts at baseline. Our findings were similarly robust to assuming extreme values for the districts linked to excluded applications and to accounting for missingness using multiple imputation (**Table 10**, Appendix Table A4).

DISCUSSION AND CONCLUSIONS

MAIN FINDINGS

In this national analysis of the effects of the US EPA's School Bus Rebate Program, we found evidence that replacing the oldest school buses with newer, lower emission buses was associated with increases in school-district attendance rates, improvements in educational achievement for their students with respect to RLA and math, and lower ambient $PM_{2.5}$ concentrations in the communities surrounding the school districts. Little evidence was found for the benefits of replacing newer buses, and there was no consistent evidence that clean bus funding reduced respiratory-related ED visit rates overall among 5–18-year-olds on Medicaid, although these models were sensitive to model specification.

Our findings are noteworthy as this is, to our knowledge, the first evaluation to assess the effectiveness of the national US EPA School Bus Rebate Program. Additionally, the randomized allocation of funding by the US EPA provides strong support for a causal interpretation of the effects of school districts switching to cleaner, lower-emission buses. This work demonstrates that the program had positively affected student attendance, educational achievement, and air quality across the nation, especially when the oldest buses were replaced.

The beneficial effects of replacing buses of the oldest model years found consistently throughout this research, are both important and unsurprising given the increasing strictness of emissions standards for buses in the United States over time. For context, US EPA standards for buses required an approximate six-fold reduction in PM emissions for 1991–1997 model-year buses compared with 1990 and older model-year buses. There were smaller reductions in emissions required by the regulatory standards in 1998, 2004, and 2007.[57] Although this indicates that the overall effects of this program may decline over time if there are no further improvements to cleaner bus technologies, the value of this program is likely to continue for many years, given that the average school bus is on the road for 16 years before being decommissioned.[22] For example, in the 2020s we estimate that approximately 1% of the US fleet (3,500 buses) were pre-1990 buses while approximately 10% of the fleet (35,000 buses) were 1990–1999 model year buses.[23,24,58] This translates to over 250,000 students riding pre-1990 model year buses and almost 3 million students riding a pre-2000 model year bus to school.[24] Given that the benefits were predominantly observed for the replacement of the oldest buses, it may be that the benefits of this program will become smaller over time, and that the sustained effects of school bus replacements should be ascertained after the fleet has fully transitioned to newer buses.

Overall, this work suggests large measurable population gains with the replacement of older buses. For example, we estimate that replacement of all pre-1990 model year buses across the United States could lead to over 400,000 additional student days of attendance each year (408,729; 95% CI: 232,103 to 585,446), while replacement of 1990s model year buses could result in over 900,000 additional student days of attendance each year (918,311; 95% CI: –236,343 to 2,072,964). Such attendance benefits are important with respect to avoided caregiver costs for younger children and lost learning for middle school and high school students. Using the US EPA's estimated value of a lost day of school of \$1,000,[55] we estimate that replacing all buses in the United States that were manufactured before 1990 could lead to \$400 million in economic benefits per year; replacing all of the buses manufactured before 2000 could lead to \$1.3 billion in economic benefits per year. Given that we also estimated that there were over 350,000 additional student days of attendance per year in the districts linked to applications selected in the lottery (351,093; 95% CI: –70,678 to 772,865), this implies that the total investment of \$27 million by the US EPA for the 2012–2017 lotteries likely resulted in \$350 million of benefits per year due to reduced absenteeism alone. At an estimated cost of around \$78 per additional day of student attendance, this represents a fraction of the cost for other absenteeism interventions, such as mentorship programs that cost approximately \$500 per additional day of student attendance and improved student attendance by 0.4 pp.[41] The US EPA program, however, is more expensive than a simpler intervention that shared student absenteeism information with parents, costing only \$6 per additional day of student attendance and improving attendance by 0.3 pp.[42] On the other hand, given costs of up to \$300,000/bus,[21] the pre-1990 buses could be replaced by an investment of approximately \$1 billion, which reflects about one fifth of the budget already allocated to the US EPA's new Clean School Bus Program over the next 5 years to replace existing school buses with zero-emission and low-emission models.[59] Importantly, it is likely that districts with the oldest buses are those with the least resources to upgrade buses without the US EPA funds.

When considering educational performance, we observed improvements in test scores when the oldest school buses were replaced. The magnitude of the effect of US EPA fund-

Table 10. Effects of School Bus Replacements on Ambient $PM_{2.5}$ Concentrations in Secondary and Sensitivity Analyses

	Primary Model[a]		Change in Outcome[b]		Adjusted for Free and Reduced-Priced Lunch Eligibility[c]	
Model	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**
Overall effect of replacement	–0.04	–0.11, 0.04	–0.06	–0.14, 0.02	–0.02	-0.09, 0.05
Effect of replacement for different model years of replaced buses[g]						
pre-1990	–0.95	–1.45, –0.45	–1.11	–1.64, –0.59	–0.91	–1.57, –0.24
1990–1999	–0.04	–0.15, 0.08	–0.04	–0.16, 0.07	–0.02	–0.14, 0.10
2000 and newer	–0.01	–0.08, 0.06	–0.03	–0.11, 0.04	–0.02	–0.09, 0.05
Number of observations	2,991		2,991		2,810	

	Adjusted for Changes in School District Characteristics[d]		Adjusted for Baseline Levels of Other Outcome Measures[e]		Multiple Imputation[f]	
Model	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**	**Parameter Estimate**	**95% CI**
Overall effect of replacement	–0.03	–0.11, 0.04	–0.03	–0.13, 0.06	–0.04	–0.11, 0.03
Effect of replacement for different model years of replaced buses[g]						
pre-1990	–0.90	–1.54, –0.27	–1.24	–1.45, –1.04	–0.95	–1.28, –0.61
1990–1999	–0.02	–0.14, 0.10	0.08	–0.04, 0.20	–0.04	–0.15, 0.07
2000 and newer	–0.02	–0.09, 0.04	–0.08	–0.18, 0.03	–0.01	–0.10, 0.09
Number of observations	2,763		1,981		3,019	

[a] Dependent variable is the $PM_{2.5}$ in the year after the lottery. Model is adjusted for the $PM_{2.5}$ in the year before the lottery, US EPA Region, lottery year, and an indicator for having more than one application in a given lottery year.

[b] Dependent variable is the difference in $PM_{2.5}$ in the years before and after the lottery. Model is adjusted for US EPA Region, lottery year, and an indicator for having more than one application in a given lottery year.

[c] Primary model, additionally adjusted for district free and reduced-priced lunch eligibility rates.

[d] Primary model, additionally adjusted for the difference in the district number of schools, number of students, percentage of students that are White, and the free and reduced-price lunch eligibility rates in the years before and after the lottery.

[e] Primary model, additionally adjusted for baseline levels of district average attendance rate, RLA and math standardized scores, and respiratory-related ED visit rates among 5- to 18-year-old Medicaid beneficiaries.

[f] Primary model including observations with previously missing outcome measures newly estimated with multiple imputation methods.

[g] Independent variables of interest are indicator variables for selected districts replacing buses with average model year pre-1990, 1990–1999, and 2000 and newer.

ing on RLA test scores was roughly equivalent to 25%–30% of the observed effect on test scores for a reduction in class size of 7–10 students.[60,61] These findings are plausible, given evidence that air pollution can directly affect cognitive performance in children.[62-65] They are also consistent with our attendance results because school attendance has repeatedly been associated with student achievement.[38,66-70] Interestingly, however, we did not find evidence that our educational performance results were mediated by attendance. This lack of an observed mediative effect of attendance on education in our analysis might be a result of the fact that, because of issues with power, we evaluated mediation on the whole population of replacements as opposed to only the oldest buses. The coarse resolution of both datasets may have also limited our ability to detect mediation statistically. Additionally, there is some mismatch between the two sources because the attendance data represents the experience of all enrolled students (i.e., kindergarten through 12th grade), while the educational performance data represents only 3rd- through 8th-grade students. If the effects of funding on attendance were distributed unevenly across age groups, it would be unsurprising that K–12 attendance rates did not mediate the relationship between clean bus funding and 3rd- through 8th-grade test scores.

Beyond the benefits of bus replacement observed for children attending participating schools, there was some evidence of broader effects on air pollution levels in the community. Specifically, we observed a 1-μg/m^3 reduction in $PM_{2.5}$ concentrations in districts replacing the oldest buses. Given a population-weighted $PM_{2.5}$ concentration of 8 μg/m^3 for the United States during our period of study,[71] this translates to a sizeable reduction. Although surprising in magnitude, the results were robust across many different specifications of the model and under numerous sensitivity analyses, thus raising our confidence in the results.

Interestingly, despite the large apparent changes to ambient air in the community, we saw no evidence that being selected for Clean School Bus Funding was associated with reduced respiratory-related ED visit rates among 5–18-year-olds on Medicaid, even for districts replacing the oldest buses. We even saw the suggestion of increases in respiratory-related ED visits for districts linked to applications that were awarded funding. However, these results were imprecise, sensitive to model specification (especially correction for missing data), and did not have the same consistent dose–response function as observed for other outcomes, perhaps supporting a null finding. A null finding would be reasonable if diesel exhaust from school buses resulted in more minor disruptions to health that cause children to miss school rather than to need an ED visit. Bias is another possible explanation for these null and inconsistent findings for the ED visits. First, it is possible that measurement error may have played an important role in our analysis because the Medicaid data were of substantially lower quality than the attendance and educational performance data, which are specific to the children attending the schools in the districts linked to the US EPA applications. The Medicaid data only represent the subset of children eligible for this government assistance program and can include children who attend private schools or have other schooling arrangements. While we would expect these sources of misclassification to bias our findings toward the null, our sensitivity analysis that was limited to the zip codes completely contained within school district boundaries did not indicate a stronger reduction in ED visits in districts linked to selected applications. Finally, we found evidence that these findings may have been magnified because of selection bias resulting from the post-randomization exclusion of applications linked to missing school districts and residual confounding by changes in demographics in the years before and after the lottery. This differs from the other outcomes that were largely unaffected by further control for changes in demographics over time and accounting for missingness by multiple imputation.

COMPARISON TO PAST RESEARCH

To put our results in context with our earlier research, we compared the current study's findings for attendance to those of our previous observational panel study in the Washington State Puget Sound area, which evaluated the effects of school bus retrofits on school attendance of individual children.[17] Similar to the current study, in our earlier work we found that students experienced a reduced risk of absenteeism in the previous month when they were riding newer, lower-emission buses compared with older, higher-emission buses. Austin and colleagues[35] used an ecological study of observational data from Georgia to investigate school bus retrofits on absenteeism; they reported an estimated 0.03-pp increase in attendance for districts with the average level of fleet retrofits (19%).

Our education findings are also similar to — but less precise than — the Austin et al. investigation with respect to the educational effects of a school bus retrofit program.[35] In that work, the researchers reported that a district that retrofitted 19% of its fleet (the average percentage retrofitted across its sample) had an average increase in English language arts and math scores of 0.017 (95% CI: 0.0057 to 0.028) and 0.009 (–0.0019 to 0.02) SDs, respectively.[35] A second unpublished study assessed the effects of a separate US EPA competitive grant program that also funded school bus retrofits and replacements[37] and reported improvements in standardized testing similar to those of Austin et al.[35] These improvements are approximately three times smaller than the associations that we observed for districts that replaced pre-1990 model-year buses, but they are larger than our overall effects.

Our health results differ from the existing work on this topic. For example, one study used an ecological difference-in-difference design to assess the effects of school bus retrofits in Washington State on health.[36] In this observational study, Beatty and Shimshack[36] found that school bus retrofits were associated with reduced community-wide hospitalizations for bronchitis, asthma, and pneumonia among children with chronic conditions. This restriction to children with a chronic health condition may have increased their ability to see an effect, whereas our results may have been diluted by including all children in our study sample. A second observational study in Georgia showed that children in school districts that retrofitted their school buses had larger increases in aerobic capacity on state-required physical activity tests,[35] and our work in Washington State[17] found significant improvements in inflammation of individual riders due to bus retrofits. These studies perhaps were better powered to detect associations if these subclinical measures were more sensitive to changes with diesel exposures than ED visits.

Finally, in terms of air quality, one unpublished study looked at the national-level effects of a separate US EPA competitive grant program, which also funded school bus retrofits and replacements.[37] The author observed small improvements in $PM_{2.5}$ concentrations after the retrofits. Specifically, in districts that retrofitted the average number of school buses (n = 73), $PM_{2.5}$ concentrations decreased by 0.05 μg/m^3 as a result of the retrofit program. The smaller magnitude of these results compared with ours may be due to the study looking only at bus retrofits, whereas ours almost exclusively evaluated school bus replacements.

LIMITATIONS

One key limitation of this work is that our results are for the school-district level and thus include both children who ride the bus and those who do not. In general, we expect that this will likely underestimate the true effect on students who were directly affected by the change to new, lower-emission buses. We see evidence of this phenomenon when we compare the results of the current study with those of our previous panel study of bus riders in the Washington State Puget Sound.[17] In that repeated-measures study, we found that students experienced a 5% to 15% reduction in the risk of absenteeism in the previous month and less lung inflammation when they were riding newer, lower-emission buses compared with older, higher-emission buses.[17] When assuming a binomial distribution, we see that these reductions estimated at the individual student level are approximately 1.25 times stronger than our primary attendance results when estimated at the school district. Further evidence of the dilution of the effects for individual riders comes from our findings of a near dose–response relationship across quartiles of estimated ridership levels on the buses requested for replacement in our attendance outcome. In fact, we observed an order of magnitude greater increase in attendance in districts with the highest versus the lowest quartile of estimated bus ridership, although these groups could not be statistically distinguished from one another. Interestingly, we did not observe a similar dose–response relationship by ridership levels for educational performance although there was some suggestion, but not statistically significant evidence, of greater reductions of ambient $PM_{2.5}$ with increasing numbers of buses replaced.

Importantly, the observed associations in this study tell a compelling and consistent story, especially for the oldest buses. Our overall associations, however, were often imprecise and not statistically different from no association. When planning this study, we had expected to have sufficient power to detect differences between selected and nonselected districts given associations observed among school bus riders.[17] As described above, however, the dilution of our results across all students resulted in the observed associations being much smaller than we had anticipated based on research in only bus riders. When updating our power calculations with the observed associations in this study, we see that we had only about one tenth of the applications needed to detect statistically significant associations. This lack of power is an important consideration when interpreting findings that were not statistically significant. It also highlights the need for future work that includes more recent years of the US EPA Clean School Bus Funding Program to increase statistical power.

Another potential source of bias toward the null in this work is our use of the ITT approach. Although districts linked to 35 included applications selected for funding ultimately did not purchase a new bus due to difficulty acquiring matching funds, based on the ITT approach our analysis treated these applications as selected lottery applications. Similarly, districts linked to applications not selected for funding could have replaced or retrofitted buses outside of this program, but they were treated as unselected in our analysis. Analyzing the data in this way will result in a lower bound for the true associations between being selected to receive Clean Bus Rebate Funding and each of our outcomes of interest.[72] We used an ITT approach to retain the randomized allotment of Clean Bus Funding, which provides much stronger evidence of the causal effect of school districts switching to newer, lower-emission, school buses. This differs importantly from previous studies in this area, which have relied on districts self-selecting bus replacements. This lack of random assignment in previous studies raises the possibility that there were fundamental differences between the school districts that adopted newer, lower emission buses, or the times when newer buses were used, compared with districts that did not adopt newer buses or the times when newer buses were not used due to some other characteristics that are important to health, education, and air quality. In contrast, our design reduces concerns of confounding by measured or unmeasured school-district-related characteristics. In fact, we see that with respect to all key demographic characteristics evaluated, there was even balance achieved between the districts linked to selected and unselected applications. Although we observed some differences in a few of our outcomes between the districts linked to selected and unselected applications in the year before the bus replacement, all of our models used paired data before and after the switch, thus accounting for any differences by school districts that were not eliminated by randomization (i.e., occurred due to chance alone). We also found that our key take-home messages were unaltered by adjustment for baseline outcome levels. This further bolsters the causal interpretation of our findings.

An additional point of note is that our inclusion criteria (see Figure 2) were applied after the randomization. This could raise selection-bias concerns. It was not anticipated that this would distort the randomization, however, because our exclusion criteria should be unrelated to lottery selection status. In fact, we found no evidence that being excluded was related to the likelihood of being selected for funding (Appendix Table A5). Nonetheless, we attempted to investigate the importance of this exclusion in sensitivity analyses. First, we found that our results were robust to even extreme changes in assumed values of the outcome for the districts linked to excluded applications (Appendix Table A4). Second, we found that imputing data for those districts linked to excluded applications for missing outcome information did not change our results, with the one exception of our analysis of ED visits. For this one outcome, the overall findings flipped from suggesting a counterintuitive, hazardous relationship with being selected for new buses to the anticipated protective one, suggesting that there may have been some selection bias at work for this outcome. Nonetheless, the robustness of our other results mitigates concerns of selection bias due to the exclusion of applications, post-randomization for our attendance, educational performance, and community air pollution results.

As a final note, we mention that this work only investigated the replacement of older diesel school buses with new diesel school buses. Virtually all districts linked to selected applications (379 of the 380 with available data) purchased a new bus as opposed to installing retrofit technology (Appendix Table A3). In addition, none purchased electric buses, so we are unable to conclude if these results would be the same for those replacements. Similarly, we are unable to make any conclusions about the sustained benefits of this program over time, given our focus on outcomes in the year following the bus replacement. Relatedly, our findings were strongest for the smaller number of districts with the oldest buses. Because the number of districts with pre-1990 and pre-2000 buses will continue to decrease over time, the benefits of this program may weaken as these oldest buses are decommissioned. In addition, the bus age data were only available to us as the average age of all replaced buses rather than the individual ages of each bus. Averages can be sensitive to outliers compared to the median, therefore it is possible there was exposure group misclassification in terms of model years of the replaced buses. Such misclassification would likely have made it even more challenging to accurately detect the true effects.

It is also the case that entrants to the US EPA School Bus Rebate Program differed from the entire population of US school districts in terms of size and student makeup. On average, districts linked to applications to the lottery were larger, of higher income, and had a greater fraction of white students. Given that the size of a district influences the proportion of children who will be able to ride the new buses, our overall results might represent an underestimate of the effects in other school districts. The different demographics of districts linked to entrants that applied for funding also suggest that the program may not have benefited the most socially vulnerable children. Relatedly, there could be generalizability concerns in our extrapolation of impacts to the full US school district population if the entrants to the US EPA School Bus Rebate Program during the time period evaluated had fundamentally different responses to the replacement of buses than did other locations. Possible reasons for such differences would be different ages of buses, different baseline health status of the students, or different durations spent on the buses. When possible, we evaluated effect modification of our findings by these factors.

IMPLICATIONS OF FINDINGS

The findings in this work, which were conducted using a causal framework given the US EPA's random allotment of funding, indicate that the US EPA's School Bus Rebate Program has improved district-level student attendance, educational performance, and air quality in the districts that removed the oldest buses. Focusing on attendance alone, our results suggest that the total investment of $27 million by the US EPA for the 2012–2017 lotteries may have resulted in $350 million of benefits per year due to reduced absenteeism alone, although these benefits could not be distinguished from no benefit. Therefore, we conclude that the US EPA's School Bus Rebate Program investments to remove the oldest buses with the highest emissions from the fleets have positively affected communities. Assuming that the districts linked to applications in the lotteries studied in this report are representative of bus replacements throughout the nation, we estimate that investing funds to replace all school buses in the United States manufactured before 1990 could lead to an additional $400 million in economic benefits per year, and replacing all US school buses manufactured before 2000 could lead to an additional $1.3 billion of economic benefits per year.

DATA AVAILABILITY

Data and code pertaining to all analyses in this report are available at *https://doi.org/10.7302/sjy5-0540*. Please note that attendance data is masked for two states with data agreements, which precluded us from sharing the data publicly. Additionally, the respiratory ED visit data is omitted from the posted data due to the data agreement for this health outcome.

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HEI QUALITY ASSURANCE STATEMENT

The conduct of this study was subjected to an independent audit by Westat staff members, including experienced quality assurance (QA) auditors with expertise in statistical modeling, epidemiology, exposure assessment, and geographic information systems analysis. The Westat QA audit team consisted of Dr. Daniel Chacreton, Dr. Joseph Abraham, Dr. David Wright, Dr. Brandon Hesgrove, and Ms. Rebecca Birch. These staff members are highly experienced in quality assurance oversight across various relevant domains.

The QA oversight program for this study involved a comprehensive evaluation of the Draft Final Report for evidence of updated methodology, reanalysis, or clarification of data that was previously noted as requiring enhancement in the initial review by the HEI technical review committee. The specific details of the dates of the audit and the types of reviews performed are outlined below.

FINAL REMOTE AUDIT

Date: February 2024 – August 2024

Remarks: The Adar et al. study underwent an independent quality assurance (QA) audit conducted remotely by the Westat QA team. The audit was led by a diverse group of experts specializing in areas crucial to the study, including the quality of the documentation of the study methods, fidelity to the data analysis plan, and the accuracy and clarity of the study results and conclusions.

The QA oversight program was initially designed to include both an on-site audit to assess adherence to the study protocol and standard operating procedures, and a final remote audit to evaluate the processing of data, statistical analyses, and the reporting of study findings. However, due to logistical constraints, the on-site audit was not conducted. Instead, the audit team focused on a thorough remote assessment, examining the processes related to data collection, statistical analysis, the accuracy of data presentation, and the appropriateness of the study conclusions as presented in the Draft Final Report.

The Westat QA review of the Adar et al. study concentrated on several critical aspects:

- Adherence to the study protocol and the robustness of the documentation of study methods, including data processing, exposure modeling, and statistical analysis.
- The adequacy of addressing study assumptions and limitations, such as potential confounding factors, biases, and the consistency of the results with the data collected.
- Whether the investigators' conclusions were justified based on the study findings, considering any limitations noted during the audit.
- The clarity and comprehensibility of the report to ensure that it could be easily understood by its intended audience.

Following their review, the Westat QA audit team provided detailed feedback in a written report to HEI and the study investigators. The audit team found that the study was generally well conducted, with the final report accurately reflecting the study's procedures and outcomes. However, the auditors provided several recommendations for improvement. These recommendations included

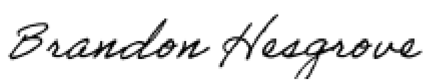
- Re-evaluating study power calculations using updated effect size estimates.
- Clarifying in the report when model results are nonsignificant, ensuring that readers understand no association was detected.
- Specifying whether the reported sample size represents the number of school districts or the number of applications submitted.
- Increasing clarity and interpretability of report text, figures, and tables. Including defining terms like 'dirty' and 'clean' school buses and indicating if data on the number of buses replaced/retrofitted were available and used in the analysis.

Dr. Adar and her team responded to the QA recommendations, incorporating the feedback into a revised final report that was subsequently reviewed by HEI and provided back to Westat. The Westat QA audit team attests that the final report accurately represents the study conducted and that the recommendations provided have been appropriately addressed. The final report appears to be a reliable and clear reflection of the research and its findings.

Daniel Chacreton, PhD, Statistician, Quality Assurance auditor

Joseph Abraham, ScD, Epidemiologist and Environmental Scientist, Quality Assurance auditor

David Wright, PhD, Statistician, Quality Assurance auditor



Brandon Hesgrove, PhD, Health Economist, Quality Assurance auditor

Rebecca Jeffries Birch, MPH, Epidemiologist, Quality Assurance auditor

Date: August 22, 2024

SUPPLEMENTARY APPENDIX ON THE HEI WEBSITE

Appendix A contains five tables and one figure not included in the main report. It is available on the HEI website at *www.healtheffects.org/publications.*

Appendix A: Supplementary Tables and Figure

ABOUT THE AUTHORS

Sara D. Adar is professor and associate chair of epidemiology at the University of Michigan School of Public Health. She has an MHS in environmental health sciences from the Johns Hopkins School of Public Health and a ScD in exposure, epidemiology, and risk from the Harvard School of Public Health. Dr. Adar uses modern principles of epidemiology, environmental health, exposure science, and biostatistics to characterize the effects of environmental hazards on human health. Her research primarily focuses on the effects of air pollution and noise on healthy aging, with additional interests in global health, extreme weather events, and intervention strategies to improve health. She currently leads several large cohort studies on the effects of exposures on cognitive aging and dementia, and she also has a history of studying the effects of clean fuels and technologies on buses through her work on the Seattle School Bus Study.

Richard Hirth is professor of health management and policy at the University of Michigan School of Public Health. He received his PhD in economics from the University of Pennsylvania. Dr. Hirth's research interests include the economics of end-stage renal disease care, health insurance design and healthcare spending, the role of not-for-profit providers in healthcare markets, and long-term care. His research underlies Medicare's payment system for kidney dialysis.

Adam Szpiro is professor of biostatistics at the University of Washington School of Public Health. He has an ScM and a PhD in applied mathematics from Brown University. A major focus of Dr. Szpiro's research is developing statistical methods for environmental epidemiology and applying these methods to studies of air pollution in major cohort studies such as MESA Air, the NIEHS Sisters Study, and the Women's Health Initiative. Current methodological projects include spatiotemporal exposure modeling, measurement error correction, optimal exposure prediction modeling for health effect inference, dimension reduction for spatially misaligned data, and control for unmeasured spatial and/or temporal confounding.

Meredith Pedde is an assistant research scientist in the department of epidemiology at the University of Michigan School of Public Health. She has an MPP in environmental policy from the University of Michigan School of Public Policy, an MA in statistics from the University of Michigan, and an MPH and a PhD in epidemiology from the University of Michigan School of Public Health. Prior to attending the University of Michigan School of Public Health, Dr. Pedde worked at the US EPA Office of Transportation and Air Quality for 8 years. Her dissertation focused on air pollution epidemiology to support environmental regulations and policies, including portions of the analyses presented in this report.

OTHER PUBLICATIONS RESULTING FROM THIS RESEARCH

Pedde M, Szpiro A, Hirth R, Adar SD. 2024. School bus rebate program and student educational performance test scores. JAMA Net Open 7(3):e243121; *doi:10.1001/jamanetworkopen.2024.3121.*

Pedde M, Szpiro A, Hirth R, Adar SD. 2023. Randomized design evidence of the attendance benefits of the EPA School Bus Rebate Program. Nat Sustain 6:838–844; *https://doi.org/10.1038/s41893-023-01088-7*.

Research Report 221, *Assessing the National Health, Education, and Air Quality Benefits of the United States Environmental Protection Agency's School Bus Rebate Program: A Randomized Controlled Trial Design*, S.D. Adar et al.

INTRODUCTION

Governmental regulation is essential for protecting environmental quality and human health, but also typically incurs an economic cost. It is therefore essential to understand whether environmental policies result in the intended improvements. The area of study known as environmental accountability research evaluates the extent to which environmental regulations have yielded improved air quality and public health. A major challenge in this research field is isolating changes that can be attributed to the policy in question from improvements that might be due to other unrelated regulations or long-term trends. This challenge is a particular concern when policies target numerous pollutant sources, affect large geographic regions, and take several years to fully implement.

Over the past two decades, HEI has emerged as a leader in air pollution accountability research, contributing to research design, funding, study oversight, and evaluation of such research (see *Preface*). Through a series of Requests for Applications (RFAs*), HEI has now funded more than 20 studies that assessed a wide variety of regulations targeting both point and mobile sources of air pollution. For practical reasons, earlier studies tended to focus on local-level actions that were implemented over a relatively short time frame. HEI later solicited research that evaluated actions with a larger geographical scope or that were implemented over longer timeframes.

In its 2018 research solicitation, RFA 18-1, "Assessing Improved Air Quality and Health from National, Regional, and Local Air Quality Actions," HEI aimed to fund empirical studies to assess the health effects of air quality actions (regulatory and other air quality interventions and natural experiments) or to develop methods required for, and specifically suited to, conducting such research and make them accessible and available to other researchers. Areas of interest included national- or regional-scale regulatory actions implemented over multiple years, local actions targeted at improving air quality in urban areas with well-documented air quality problems, and regulatory programs to improve air quality around major ports and transportation hubs and corridors.

In response, Adar and colleagues proposed to assess the effects of school bus retrofit and replacement funding opportunities as part of the United States Environmental Protection Agency's (US EPA's) National Clean Diesel Rebate Program on student health and educational performance. To facilitate the transition of school districts to lower-emitting school buses, the US EPA funded fleet owners to replace or retrofit old, higher-emission, diesel-powered school buses. The program started with a pilot in 2012, and school bus replacement programs have continued in various forms to date. A random lottery approach is used to allocate the funds. Dr. Adar and colleagues planned to take advantage of the randomized allocation of funding to evaluate the effect of the program on school attendance and educational performance. They later added aims on emergency department visits for respiratory causes and community air pollution levels at the request of HEI's Research Committee.

The HEI Research Committee recommended the proposal by Adar and colleagues for funding due to its strong study design with testable hypotheses. The Committee liked that the study would evaluate a national program with policy relevance using a clearly defined and randomized intervention and well-defined outcomes. They also appreciated the approach of using an intention-to-treat analysis (explained below) that leveraged randomized selection of school districts for funding, which was a unique opportunity in environmental epidemiology. The Research Committee also liked the inclusion of student absenteeism as a potential mediator of educational performance and the sensitivity analyses proposed by the investigators to evaluate some underlying assumptions of the study.

This Commentary provides the HEI Review Committee's evaluation of the study. It is intended to aid the sponsors of HEI and the public by highlighting both the strengths and limitations of the study and by placing the Investigators' Report into scientific and regulatory context.

Dr. Sara D. Adar's 3-year study, "Assessing the National Health and Education Benefits of the EPA's School Bus Retrofit and Replacement Program: A Randomized Controlled Trial Design," began in January 2020. Total expenditures were $545,277. The draft Investigators' Report from Adar and colleagues was received for review in April 2023. A revised report, received in September 2023, was accepted for publication in October 2023. During the review process, the HEI Review Committee and the investigators had the opportunity to exchange comments and clarify issues in both the Investigators' Report and the Review Committee's Commentary. Dr. Adar is a member of the HEI Review Committee and has been recused from all discussions of the report.

* A list of abbreviations and other terms appears at the end of this volume.

SCIENTIFIC AND REGULATORY BACKGROUND

SCHOOL BUS EXPERIENCES OF STUDENTS IN THE UNITED STATES

Every day, school buses transport 20 to 25 million children, including 50% of all pre-high school students and 60% of low-income students, to and from primary and secondary schools in the United States.[1–3] Nationwide, in 2019 and 2020, students attending traditional public schools who rode school buses rode about 25 minutes each way to school, with 75% of students riding school buses for less than 30 minutes.[4] However, the experience of riding the school bus varies geographically, by race, and by family income, with rural and minority children typically experiencing longer bus rides. A survey of 1,194 elementary school principals in five states (Arkansas, Georgia, New Mexico, Pennsylvania, and Washington) reported that students who attended rural elementary schools were more likely to be eligible to ride school buses than were students attending urban schools.[5] Compared with students who attended suburban schools, those attending rural schools also had longer bus rides — lasting 30 minutes or more each way with rougher ride conditions — than suburban school students. One of the most studied cities for student transportation is New York City, where typical lengths of school bus rides were in line with national averages.[6] In New York City, public school students who rode school buses were more likely to be Black or Hispanic and to attend choice or charter schools (thus traveling farther to school). They had disproportionately longer travel times to school compared with students who used public transportation or arranged private transportation.[6,7] With many children spending at least an hour per day on school buses, their exposure to emissions from the school buses, particularly those with old, highly emitting diesel engines, and to traffic emissions generally, is of concern.

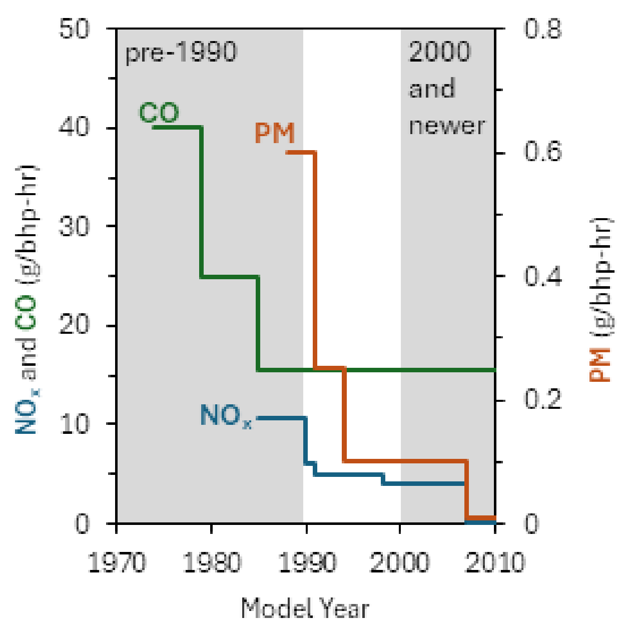
DIESEL EMISSIONS FROM SCHOOL BUSES

About 89% of the half million school buses currently in use are powered by diesel fuel.[8,9] Increased concentrations of air pollutants — including fine particulate matter ≤2.5 µm in aerodynamic diameter ($PM_{2.5}$), black carbon, ultrafine particles, and carbon monoxide (CO) — from diesel exhaust have been reported near idling school buses during student pickup and drop-off and inside the buses themselves, including in previous research funded by HEI.[10,11] Diesel exhaust has been classified by the International Agency for Research on Cancer as a known human carcinogen,[12] and exposure has been associated with increased risks of adverse respiratory symptoms, hospitalizations related to heart and lung illnesses, and premature death.[13]

To reduce these emissions, the US EPA implemented substantially more stringent emissions certification standards for school bus and other engines starting with model year 1985 for CO and starting with model year 1990 for PM and nitrogen oxides (NO_x) (**Commentary Figure 1**). Following on earlier reductions, the most recent emissions requirements of 2007 and 2010 have substantially improved emissions of PM and NO_x and alleviated some of the associated health concerns.[14–17] These latest improvements were possible because of a combination of new technologies and fuel standards. For example, diesel particulate filters and selective catalytic converters became standard in new diesel engines in 2007 and 2010, respectively. Supporting the effectiveness of these technologies and also reducing PM formation on its own, the US EPA implemented fuel requirements to reduce PM emissions and to protect catalytic converters, including the phase in of ultra-low sulfur diesel starting in 2006.[18] Most states have also implemented rules to address air quality issues associated with idling of school buses and other vehicles.[19]

As a result of the decreases in allowable emissions from new diesel engines over time, newer model year diesel engines used in school buses and other vehicles have substantially lower emissions of air pollutants such as CO, PM, and NO_x than do older diesel engines. However, many old school buses remain on the road. School buses are currently retired at an age of about 15 years, and in 2023, the average age of school bus fleets was just under 9 years with 67% of diesel school buses having the newest model year 2010 or newer technologies.[9,20,21] Overall, about 1% of the school bus fleet in the early 2020s were pre-1990 model years.[22] As of 2022, about 3% of buses were 1999 and older model years, and at least 8% of buses were of unknown age.[23]

Several studies have demonstrated decreased air pollutant emissions from school buses with new technologies. Tests of



Commentary Figure 1. Changes in US emissions standards for CO, PM, and NO_x from heavy-duty highway compression ignition engines (as used in school buses) over time. (Data from US EPA 2016.)

new school buses that use lower-emitting diesel technologies (e.g., diesel particulate filters and selective catalytic conversion), alternative fuels (e.g., condensed natural gas and liquefied petroleum gas), and electric power have shown reduced emissions of NO_x compared with older diesel buses.[24] Additionally, retrofitting older buses with newer emissions control technologies such as diesel oxidation catalysts or crankcase filter systems can reduce exhaust (i.e., tailpipe and engine) emissions in some cases.[10,25] Calibrating the emissions control technology and testing the same bus before and after the retrofit were both important to see these effects. Although exhaust emissions have decreased with new technologies and power sources, in-use real-world emissions continue to be higher than laboratory-based emissions certification standards.[24]

EFFECT OF REDUCING SCHOOL BUS EMISSIONS ON CHILDREN

The relationship between reduced emissions and changes in children's exposures has been less clear. A study in Washington (by the authors of the current study) found lower fine and ultrafine particles on school buses after diesel oxidation catalysts, closed crankcase ventilation systems, and ultra-low sulfur diesel fuel were adopted.[26] However, in a separate study of a small sample of diesel-powered school buses in the United States, retrofitting buses with a diesel oxidation catalyst, a crankcase filtration system, or both resulted in substantially reduced exhaust concentrations of ultrafine particles, black carbon, and $PM_{2.5}$ during idling but did not reduce in-cabin concentrations of the measured pollutants.[10]

Studies of student health and educational performance are starting to provide evidence that school bus rides affect students' educational experience and that reducing school bus emissions can improve the educational performance and school attendance rates of students. In a study of school bus ridership in New York City, bus rides longer than 45 minutes were associated with decreased school attendance and higher probability of chronic absenteeism relative to shorter bus rides.[6] School bus emissions decreased, and English and math test scores improved after school bus retrofits in studies in Georgia.[27,28] Studies in Washington state (including by the investigators of the current study) reported improvements in student respiratory health following the implementation of lower-emitting school bus technologies and fuels, especially among patients with persistent asthma.[26,29] A recent nationwide study in the United States projected that replacing diesel model year 2005 school buses with diesel model year 2010 school buses could result in reduced attributable mortality and new childhood asthma cases and that an estimated $84,200 of health and climate benefits would be achieved for each diesel school bus replaced with an electric school bus.[30] Those benefits would be mainly realized in large cities, although there would also be some benefits in other areas.

REGULATORY PROGRAMS FOR LOWER-EMITTING SCHOOL BUSES

To reduce the potential effects of diesel exhaust on children, the US EPA provides funds to support the replacement or retrofit of older, higher-emission diesel school buses by owners of school bus fleets through various rebate and grant programs. The school bus retrofit and replacement funding opportunities evaluated in the current study were part of the National Clean Diesel Rebate Program, which was authorized by the Diesel Emissions Reduction Act (DERA) of 2010, and provided rebates for the replacement of 2006 and older model year school buses with new models of diesel, gasoline, propane, condensed natural gas, or electric school buses. Between 2012 and 2017, the US EPA awarded over $27 million to replace or retrofit school buses, and since then, the program has continued for a total of more than $66 million either disbursed or committed to school bus replacement as of April 2024.[31]

In recent years, the US EPA has run other clean school bus programs concurrently with the DERA School Bus Rebates. Those programs include the American Rescue Plan (ARP) Electric School Bus Rebates for electric school buses for underserved school districts and the Bipartisan Infrastructure Law (BIL) rebate and grant programs to replace old, higher-emitting diesel buses, with priority to fleets that serve disadvantaged communities. In most cases, the US EPA's school bus replacement programs require proof of new school bus purchases and scrappage of the old school buses, although school buses from model years 2011 that are fueled by diesel, gasoline, propane, or condensed natural gas can alternatively be sold or donated when using BIL funding to purchase new battery-electric school buses if a fleet has no diesel school buses of 2010 or older model years.

Selection of applicants for funding in the National Clean Diesel Rebate Program is determined via various lottery methods, with funding priority set by random selection. Starting in 2014, some US EPA regions (each of which includes several states and territories) contributed additional funding to the rebate program to allow the selection of additional applicants from those regions after the US EPA headquarter funds were allocated. About one third of applicants selected for funding in lottery years 2012 and 2014–2017 (there was no lottery in 2013) were allocated US EPA regional funds. The ARP and BIL lotteries have more complex procedures to target the allocation of funding, but, at the time of funding the current study, only the DERA program was in place.

The current study by Adar and colleagues took advantage of the randomized allocation of DERA funds to evaluate whether this program to replace old diesel school buses improved student health (based on school attendance and respiratory emergency department visits for school-aged children) and educational performance (based on standardized test scores), and community air quality levels, all at the school district level. Their findings inform the implementation of programs to replace the most highly polluting old school buses.

SUMMARY OF THE STUDY

STUDY OBJECTIVES

Adar and colleagues studied the effects of being selected for the US EPA's school bus retrofit and replacement funding on school attendance; standardized test scores for reading, writing, and related skills (i.e., reading/language arts, hereafter referred to as *reading*) and math; emergency department visits for respiratory causes; and community air pollution levels. They evaluated whether these outcomes had improved more in school districts that were selected for funding in the rebate funding lottery compared with those that had also applied for funding but were not selected. Specific aims of the study were as follows:

1. To quantify the effects of the rebate program funding to replace old, higher emission diesel school buses with lower-emitting, upgraded buses on (a) school attendance rates for all students and (b) emergency department visit rates for respiratory causes in school-aged Medicaid beneficiaries
2. To quantify the effects of the program on standardized test scores
3. To quantify the effects of the program on community-level, outdoor air quality represented by $PM_{2.5}$

The investigators used a randomized controlled design that took advantage of the randomized allocation of funding for school bus replacements and retrofits. They compared the outcomes before and after each lottery between school districts that were selected to receive the funding and other school districts that were not, regardless of which (if any) school districts replaced their buses with new models (see **Sidebar** description of intention-to-treat analysis). They used data at the school district level starting in the 2012–2013 school year — before the first randomized allocation of funding in the 2012 pilot — and ending in the 2018–2019 school year after funding from the 2017 lottery had been awarded.

STUDY DESIGN AND METHODS

Design and Approach

This study implemented a quasi-experimental design across school districts that applied for funding to replace their old diesel school buses. They used a regression modeling approach to compare outcomes in the school year during which applicants applied for funding to outcomes in the year after the funding was awarded via lottery. Applicants that were selected for funding were notified of their selection at the end of the school year and were expected to replace or retrofit their buses in the following summer. For example, 2012 lottery applicants were notified of the results at the end of the 2012–2013 school year and should have replaced their buses in the summer of 2013. Thus, the years that were analyzed for school districts that entered the 2012 lottery were the 2012–2013 school year (*before*) and the 2013–2014 school year (*after*). Replacement buses were required to be current models for that year (e.g., model year 2012 or later for the lottery that took place in 2012). Proof of school bus purchase and scrappage of the old school bus were required to receive the allocated funds. (See **Commentary Figure 2**.)

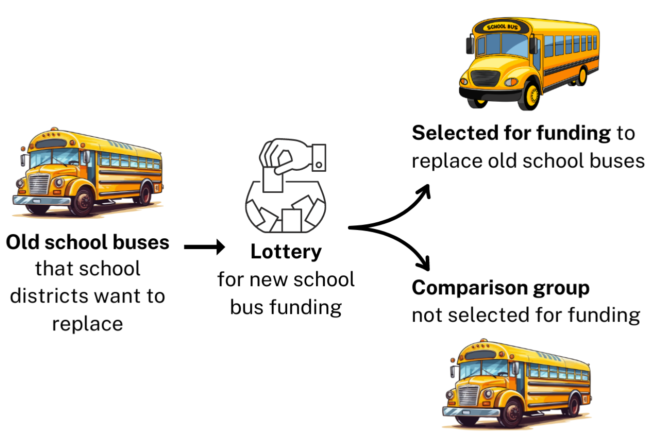
Study Population

The study population was assembled based on the dataset of individual school districts that had reporting requirements for school attendance and standardized test scores and applied for funding in 2012 and 2014–2017; there was no lottery in 2013. Therefore, applications were excluded from analyses if they (1) represented more than one school district; (2) represented private, nontraditional, or tribal schools; (3) were located outside of the continental United States; or (4) had incomplete information related to the school district that the applicant represented.

The investigators obtained the following information on the school districts represented by the lottery applicants via a Freedom of Information Act request to the US EPA: what school districts were served by applicants, how many school buses the applicants intended to replace, and whether the applicant was selected for funding through the program. For those applicants that were selected for funding, they also obtained information on characteristics of original buses, whether those were replaced or retrofitted, and confirmation of the replacements or retrofits.

Outcomes

District-level absenteeism data were obtained from the state-level departments of education, and data on school characteristics were obtained from the US Department of Education. Information on the numbers of respiratory-caused emergency department visits (i.e., asthma, upper respiratory



Commentary Figure 2. Conceptual framework of the study to assess a policy that provided funding to replace old school buses via a lottery mechanism. (Adapted from Investigators' Report Figure 1.)

Sidebar: Principles of the Intention-to-Treat Approach

The study by Adar and colleagues mimics a randomized controlled trial using intention-to-treat analysis to assess the effects of a school bus replacement and retrofit program. Intention-to-treat analysis is a method used in the medical setting to evaluate whether individual participants or groups of participants experienced a treatment effect in a placebo-controlled randomized clinical trial based on the randomly assigned treatment (e.g., a new medication, therapy, or intervention) assignment, ignoring whether or not the assigned treatment was followed and completed.[32,33] Analysts compare outcomes in the *treatment* group who were assigned to receive the treatment versus the *placebo* or *control* group who were assigned to *not* receive the treatment, regardless of the degree of noncompliance among participants in the trial. Intention-to-treat generally includes all participants that were randomized in the final analysis, even if their inclusion were later found to violate the study protocol, because excluding participants after randomization for any reason could potentially distort the randomization mechanism and bias the results, depending on the amount of exclusion and whether there were any systematic differences between the participants that were and were not excluded.[34] Intention-to-treat analysis has the benefit of retaining randomization, so it will not be subject to bias due to confounding. However, if the treatment assignments are not followed, the treated and control groups can be too similar to one another. Although the intention-to-treat approach will incorporate error if individuals or groups did not follow their random treatment assignment, the results of this misclassification will bias the results toward no association, and thus, the result will be a conservative estimate of the true effects of the treatment on the outcomes under study. As a result, intention-to-treat analysis might underestimate the effect of a treatment and can also limit the statistical power.

Some alternative approaches to intention-to-treat are to set the treatment groups based on the actual – instead of assigned – treatment of participants or to restrict the study population to only those who follow their randomized assignments.[32] In clinical trials, not all participants who are randomized to the treatment group actually follow and complete the intended treatment protocol due to side effects or other factors. At the same time, participants in the control group might make changes that affect their health or even adopt aspects of the treatment protocol (e.g., in a dietary intervention). Under perfect compliance, intention-to-treat and these alternative approaches will be the same, but if there is noncompliance the alternative approaches might differ due to confounding or selection bias.

infections, or pneumonia) among children aged 5–18 who received health coverage through the low-income Medicaid program were obtained for all zip codes intersecting applicant school districts. Standardized test score data for math and reading for children in grades 3–8 were acquired from a harmonized national dataset of student educational performance (the Stanford Education Data Archive) in December 2023. At the time of the study, standardized test scores were only available for school years spanning 2012–2017, so the final lottery year was not included in standardized test score analyses. $PM_{2.5}$ data were obtained from publicly available concentration surfaces that were modeled by combining chemical transport model predictions, ground measurements, and satellite observations on a 0.01-degree grid (roughly 1 × 1 km) and assigned to each school district for September 1 to May 31 of each school year that was analyzed.

Intention-to-Treat Analysis

The investigators took advantage of the randomized allocation of funding to conduct a study similar to a randomized controlled study (see Sidebar), where the *treatment* group was school districts with applications that were randomly selected for funding to reimburse the purchase of one or more new, lower-emission school buses and the *control* group was school districts with applications that were not randomly selected for funding.

Of the school districts that entered the funding lottery, some school districts that were selected for funding did not receive the funding and some school districts that were not selected for funding might have purchased new school buses using other funding sources. Therefore, an alternative strategy for analysis could have been to test the observed differences between districts based on whether they did replace their older, more highly emitting school buses with new school buses (see Sidebar description of intention-to-treat and alternative analyses). However, the investigators decided to use a modified intention-to-treat analysis (with some school districts excluded as indicated below) instead of an alternative approach to maintain randomization and to analyze the data in the least biased way possible.

Statistical Analyses

The main models were a modified intention-to-treat analysis where the investigators restricted their population to only those school districts with complete data on the outcomes of interest. The investigators produced multivariate regression models of student educational performance and health outcomes as a function of whether the applicant was selected for funding and other factors. Educational performance, school attendance, and air quality outcomes were modeled using linear models. Emergency department visits were modeled as a Poisson function and adjusted for population size. Each primary model was adjusted for the outcome values for the school year of the lottery (the *before* year), which year's lottery was entered, whether the applicant entered the lottery multiple times in the same year (allowed for some school districts with large fleets), and the US EPA region (because supplemental funding from some regions increased the chance of being selected for funding). Because school districts were not limited to entering the lottery in only 1 year, the investigators used general estimating equations with robust standard errors clustered at the state level to account for any potential correlation in the data.

Supplemental and Sensitivity Analyses

The investigators noted that the analyses at the school district level assumed that all children in the school district are affected by the intervention, but not all children in a district attend the affected schools, not all children ride school buses, and not all school buses in the district were replaced or retrofitted. They also noted that modeling all school districts together will estimate a common effect for replacing any old school buses, yet not all old school buses are equivalent. To address some of these differences in the treatment, they conducted analyses that were stratified by quartiles of the fraction of children who were likely to ride the buses requested for replacement and by the model year of replaced buses (pre-1990, 1990–1999, and 2000 or newer).

The investigators conducted many sensitivity analyses of such factors as properties of the school districts, accounting for prelottery levels of the outcome measures, and inclusion of observations that had been excluded due to missingness estimated using a multiple imputation approach.[35] They also conducted mediation analyses to assess whether respiratory emergency department visits mediated (i.e., were an intermediate causal step between) the effect of selection for funding to replace school buses on school attendance and educational performance.

Finally, they estimated the overall contribution of the program by multiplying the total number of students in selected school districts in the school year of the lottery by the observed primary effect estimate, and by 180 days in the school year, and extrapolated the findings to the nationwide population of school children and old school buses.

SUMMARY OF KEY RESULTS

Characteristics of the School Districts

The US EPA received 3,153 applications for funding to replace or retrofit school buses in the years 2012 and 2014–2017. Interest in new school buses substantially exceeded the available funding; therefore, only 14% of school districts that applied were selected for funding. Of the full set of applications, the analyses in the current study included 406 applications that were selected for funding and 2,613 that were not. The remaining 4% of applications were excluded based on the predetermined exclusion criteria. Standardized test score data were unavailable for about 20% of school districts in the study because of low student participation in standardized tests in some school districts and differences in test administration. Lottery status was not predictive of missingness for any of the outcomes considered.

Of those school districts that applied for the funding lottery, the proportion of each school district characteristic (e.g., size, demographics, urbanicity, and free and reduced-price lunch eligibility [a proxy for family income]), number of buses requested, school attendance rates, and standardized test scores in the years they entered the funding lottery were similar regardless of whether they were selected for funding. However, prelottery emergency department visits and $PM_{2.5}$ concentrations were slightly lower in school districts that were allocated funding than in those that were not. Compared with all 18,893 school districts in the United States, school districts that applied for the lottery funding were larger, had a higher proportion of students that were white, had a lower proportion of low-income families, and were less urban. These comparisons suggest that the results of the analyses have internal validity (i.e., the selected and not selected districts were similar) but that they cannot be easily generalized to all school districts.

Buses Replaced Following the School Bus Rebate Lotteries

Compliance with the intervention was high, with 371 of the included districts that were selected for funding (91%) providing proof of purchase of a new school bus and scrappage of the old school bus to receive the funding. Information on the type of school bus that was purchased was available for 380 of all school districts selected for funding through the program. Almost all of those school districts replaced old diesel buses with new, lower-emitting diesel buses (93.2%), with a minority choosing buses powered by other fossil fuels (6.6%). Only one school district (0.3%) installed retrofit diesel oxidation catalyst and closed crankcase ventilation technology. No school district purchased electric buses; electric school buses were largely unavailable during the study period. Information on school bus purchasing behaviors was not available for the school districts that were selected for funding but did not receive the funding or for the school districts that were not selected for funding.

Effects of the Intervention on School Attendance and Standardized Test Scores

When analyses were restricted to school districts that intended to replace the oldest, pre-1990 school buses, selection of an application for funding was associated with improved district-level school attendance and standardized test scores for both reading and math (**Commentary Figure 3**). Results for all school buses and for slightly newer buses (1990–1999 model year) showed the same trends, although these were not statistically significant. Results for the newest school buses that were intended to be replaced (model year 2000 or newer) did not show any effects on school attendance or standardized test scores.

The investigators reported that the effects on test scores were comparable to those of typical interventions to reduce class size. Additionally, they estimated that the overall magnitude of the effects was equivalent to about 350,000 additional student-days of school attendance, presumed to be because of improved health, in the school districts that were selected for funding, which they extrapolated to 1.3 million additional student-days if all pre-2000 model year school buses in the United States were replaced.

In secondary analyses, increased fractions of students riding buses did not appear to influence the association between being selected for funding and standardized test scores, although it might have influenced the association between being selected for funding and school attendance. Also, school attendance did not appear to mediate the overall relationship between being selected for funding and educational performance. In general, the sensitivity analyses with different adjustments to the epidemiological models and assumptions around the treatment of missing data corroborated the main results.

Effects of the Intervention on PM Concentrations and Emergency Department Visits

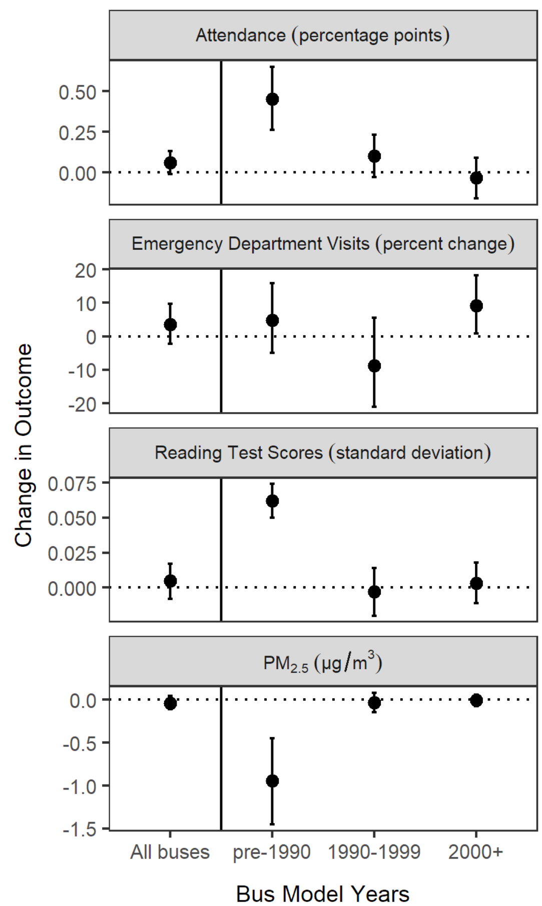
The investigators did not find an effect of being selected for funding on numbers of emergency department visits for respiratory causes in children, but these analyses were highly sensitive to model assumptions. They did find a sizable effect on community-level, outdoor air pollution — a 1-µg/m^3 reduction in $PM_{2.5}$ concentrations — in the year after the lottery in those districts that were selected for funding to replace the oldest (pre-1990) school buses. The $PM_{2.5}$ results were robust across many different specifications of the model (e.g., using the change in $PM_{2.5}$ concentration as the dependent variable instead of the $PM_{2.5}$ concentration itself) and under numerous sensitivity analyses (see above), and no alternative explanation for the unexpectedly large magnitude of the result was found.

HEI REVIEW COMMITTEE EVALUATION

In its independent evaluation of the study, the Review Committee appreciated that Dr. Adar and colleagues brought together disparate datasets to conduct a novel and useful accountability study of a program to allocate funding for replacement of old diesel school buses and presented the results in a clearly written report. They agreed with the investigators that being selected for funding appeared to improve student educational performance and school attendance, especially for pre-1990 school buses, and that the results for emergency department visits were less clear. Additionally, the Committee and investigators were not able to explain the large observed reductions in community-level, outdoor air pollution that were robust to many sensitivity analyses, because it was not clear how changing out a relatively small number of school buses could affect air quality in a school district by so much. The Committee thought that the main results for school attendance and standardized test scores were well supported by the evidence.

INTENTION-TO-TREAT AT SCHOOL DISTRICT LEVEL

The Review Committee appreciated the strong study design to test hypotheses diligently and the extensive supplemental analyses, all at the level of school districts. Leveraging a randomized funding lottery to mimic a randomized control trial and using a modified intention-to-treat approach (see



Commentary Figure 3. Effects of selection for funding to replace or retrofit school buses, stratified by school bus model year, on school attendance, emergency department visits, standardized test scores for reading, and $PM_{2.5}$ concentrations. Changes in standardized test scores for math (not shown) were similar to those for reading, but with a slightly smaller magnitude of effect.

Sidebar) to analyze the data are novel in this context. Specifically, the Committee liked the approach to compare school districts based on whether they were randomly selected for funding, regardless of whether it was known how (or whether) they chose to replace or retrofit school buses, similar to how patients are assigned treatments and analyzed in clinical studies. This approach provides an unbiased estimate of the effect of the program and does not rely on additional information (mostly unavailable) on the school buses purchased in individual school districts and school bus ridership of individual students. Additionally, detailed supplemental analyses (e.g., related to how many children potentially rode the affected school buses) and sensitivity analyses were consistent with the main results, indicating that the overall conclusions were robust.

The Committee agreed with the investigators that conducting analyses at the school district level introduces some limitations of an ecological analysis, which typically is conducted on data aggregated to groups of people (e.g., all students living within a zip code or school district or town). For example, not all children in a school district will ride buses (or more specifically, buses that have been replaced or retrofitted), and not all children will attend the schools that received new buses (because most districts have multiple schools and not all of them will receive new buses). However, the Committee emphasized that this does not invalidate the approach for measuring the effectiveness of the intervention on a population level and that the investigators have rightly recognized these limitations and attempted to address them where possible.

DEVIATIONS FROM RANDOMIZATION AND MISSING DATA

Post-Randomization Exclusion

The Review Committee and investigators noted that some exclusions of applications in the modified intention-to-treat analysis were made after the lottery randomization process. For example, some applications were excluded from the analyses because the school districts were not located in the continental United States or because there was incomplete information available on the school districts. Although the post-randomization exclusions were small (only 4% of school districts) and not related to whether the school districts were selected for funding, this modification of the intention-to-treat analysis might introduce selection bias if the exclusions were related to any of the outcomes.[34] The Committee appreciated that the investigators conducted sensitivity analyses to partially address whether post-randomization exclusions might have affected the results.

In particular, the investigators adjusted each model for prelottery levels of other outcomes considered in the study. They also replaced all excluded data with extreme values to confirm the stability of their findings to their exclusions due to missing data. They reported that the results were robust to post-randomization exclusion for school attendance, standardized test scores, and community air pollution level. However, the results for respiratory emergency department visits were not robust to the sensitivity analyses, suggesting that the findings related to emergency department visits might have been affected by changes in demographics over time, post-randomization exclusion due to missingness of data, or insufficient power to detect small effects with the available data. The Committee overall thought that the sensitivity analyses strengthened the main conclusions of the study.

Nonuniform Allocation of Funding

There were also some deviations from uniform random selection in the lottery itself, where some applicants had a higher likelihood of being selected for funding. Those deviations included the availability of extra funding in some US EPA regions and the option for applicants with large fleets to submit multiple applications. The investigators used fixed effects in their regression models to account for these differences among regions and applicants, and they also used general estimating equations with robust standard errors clustered at the state level to account for any potential correlation in the data. The Review Committee agreed that the analyses were sufficient to account for differences in probability of selection because of nonuniform allocation of funding.

Treatment of Missing Data

Separately from randomization of the allocation of funding, missing data on any variable in the models could theoretically have affected the results because the main models were based on complete-case data. The Review Committee noted that there were some baseline differences between the selected and unselected lottery applicants that might still be important. They appreciated that the investigators had confirmed that there was no association of missingness for any of the outcomes with lottery status and that the investigators reran all models after using multiple imputation together with Rubin's rule for missing outcome variables.[35] All findings except for emergency department visits were robust to accounting for missingness using multiple imputation. The Committee appreciated the analyses with imputation because these results would likely continue to be valid if the missing data were random, even if the complete-case analysis were biased.

Although the Committee would have preferred that missing data due to incomplete information on the randomized school districts and other causes could have been avoided, it appreciated the investigators' efforts to evaluate the potential impact of deviations from randomization and missing data.

FINDINGS AND INTERPRETATION

The investigators presented interesting and useful findings, including that the greatest improvements in school attendance and standardized test scores were associated with the replacement of the oldest (pre-1990) diesel school buses.

Based on these findings, the Review Committee concurred with the investigators that the program had positive effects on students' school attendance and standardized test scores. The Review Committee was puzzled by some of the results, especially for emergency department visits, where the effect was opposite (but not statistically significant) of the hypothesized direction and for community-level, outdoor $PM_{2.5}$ concentrations, where the 1-μg/m^3 reduction was much larger than expected and it was not clear how changing out a relatively small number of school buses could affect air quality in a school district by that much, given that typical $PM_{2.5}$ concentrations in the United States today are only about 8 μg/m^3. However, it is possible that students experienced lower pollution exposures while traveling on the buses, thereby affecting their school attendance and standardized test scores. The Committee thought that the interpretation of those results could benefit from further exploration.

The investigators also presented an interesting extrapolation of the potential benefits of replacing all school buses in the entire continental United States. Although the Review Committee thought this analysis was useful and agreed with the investigators that it does not account for sustained benefit over time, they thought it perhaps overestimated the potential annual benefits. First, school districts that did not enter the lottery might be less likely to replace their current school buses, even if funding becomes more widely available. Second, other differences between school districts that applied and those that did not apply for the lottery might mean that the results for the study population are not representative of most school districts, especially those that experience environmental and social justice issues and were underrepresented in the lottery applications.

The US EPA continues to fund rebate and grant programs for the purchase of lower-emitting school buses and motivates those programs in part with the benefits reported in other publications resulting from the current study.[36,37] Recently, electric buses have become more readily available and have been prioritized in the US EPA's programs to fund purchases of new school buses. At the same time, the US EPA has started to give preference to applicants in underserved districts when allocating funding.[38,39] Additionally, after the end of the study period, the COVID-19 pandemic disrupted healthcare and education, with reduced student school attendance and educational performance compared with before the pandemic.[40,41] As a result of those changes, the incremental benefits of programs to replace old school buses might change in the future. It would be valuable to update the analysis of clean school bus programs in 5 to 10 years to evaluate the benefits of replacing diminishing numbers of the oldest school buses. Additional future benefits are expected when school buses in today's fleet are replaced with the newest generation of diesel school buses, with school buses operating on other fuels, or with electric school buses.

SUMMARY AND CONCLUSIONS

Dr. Adar and colleagues conducted a thorough accountability study of the US EPA's School Bus Retrofit and Replacement Program under DERA that was administered via a lottery mechanism over the period of 2012 and 2014–2017. They linked data on school attendance, reading and math standardized test scores, emergency department visits, and community-level, outdoor $PM_{2.5}$ concentrations to compare student outcomes in school districts that were selected for funding to school districts that were not selected for funding. They reported that student educational performance and school attendance increased more in districts that were selected for funding than in districts that applied for funding but were not selected, with the highest improvements in student educational performance observed for the school districts that were selected for funding to replace pre-1990 school buses with new school buses. Improvements in community air quality were found, although the magnitude of the effect suggests the need for further research to understand their implications. Results for effects on student emergency department visits were inconsistent and need further research.

Key strengths of the study were the novel imitation of a randomized controlled trial through the application of a modified intention-to-treat approach to analyze the effect of funding being made available for new school buses, the clearly stated hypotheses, the combination of disparate datasets, and the many sensitivity analyses to evaluate factors that might have affected the statistical analyses or the effectiveness of the intervention (e.g., replacing buses versus retrofitting diesel engines and the fraction of students who rode school buses in different school districts). The Committee noted some limitations, in particular some post-randomization exclusions. However, the investigators demonstrated that the results were reasonably robust. Thus, the Committee concurred with the investigators that remaining uncertainties were unlikely to change the overall results substantially regarding the effectiveness of the program to replace old diesel school buses with lower-emitting school buses from model years that were new at the time of the lotteries.

Results of the current study provide evidence of benefits of funding for school bus replacement programs by federal and state agencies.[36,37,38] Additional focus on disadvantaged school districts and the adoption of new technologies (e.g., electric buses) is expected to reduce emissions from the oldest school buses with the highest emissions. Therefore, it would be valuable to update the analyses in 5–10 years to evaluate the effects of programs to replace more of the older diesel school buses with newer models and newer technologies, including those powered by lower-emitting diesel, other fossil fuels, and electricity. This work will be important to support the health and educational performance of schoolchildren and communities.

ACKNOWLEDGMENTS

The HEI Review Committee thanks the ad hoc reviewers for their help in evaluating the scientific merit of the Investigators' Report. The Committee is also grateful to Dan Crouse for oversight of the study, to Allison Patton and Samantha Miller for assistance with review of the report and in preparing its Commentary, to Carol Moyer and Tom Zaczkiewicz for the editing of this Report and its Commentary, and to Kristin Eckles and Hope Green for their roles in preparing this Research Report for publication.

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ABBREVIATIONS AND OTHER TERMS

CI	confidence interval
CHIP	Children's Health Insurance Program
ED	emergency department
ICD	International Classification of Diseases
ITT	intention-to-treat
PM	particulate matter
$PM_{2.5}$	particulate matter ≤2.5 µm in aerodynamic diameter
pp	percentage point
QA	quality assurance
RFA	Request for Applications
RLA	reading and language arts
SD	standard deviation
SEDA	Stanford Education Data Archive
US EPA	United States Environmental Protection Agency

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NUMBER 221

OCTOBER 2024

Health Effects Institute
75 Federal Street
Suite 1400
Boston, Massachusetts 02110, USA
+1-617-488-2300

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