NCEE Working Paper

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Working Paper 22-01
February, 2022

U.S. Environmental Protection Agency
National Center for Environmental Economics
https://www.epa.gov/environmental-economics

NATIONAL CENTER FOR ENVIRONMENTAL ECONOMICS

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February 2022

Abstract

Leaded fuel used by piston-engine aircraft is the largest source of airborne lead emissions in the United States. Previous studies have found higher blood lead levels in children living near airports where leaded aviation fuel is used. However, little is known about health effects on adults. This study is the first to examine the association between exposure to leaded aviation fuel and adult cardiovascular mortality. We estimate the association between annual piston-engine air traffic and cardiovascular mortality among adults ages 65 and older near 40 North Carolina airports during 2000 to 2017. We use several strategies to minimize the potential for bias due to omitted variables and confounding from other health hazards at airports, including coarsened exact matching, location-specific intercepts, and adjustment for jet-engine and other air traffic that does not use leaded fuel. We find that cardiovascular mortality rates within a few kilometers of single-runway airports were significantly higher in years with more piston-engine air traffic. We do not consistently find a statistically significant association between cardiovascular mortality rates and piston-engine air traffic near multi-runway airports, where there is greater uncertainty in our measure of the distance between populations and aviation exposures. These results suggest that (i) reducing lead emissions from aviation could yield substantial health benefits for adults, and (ii) more refined data are needed to obtain more precise estimates of these benefits.

Subject Areas: Toxic Substances, Health, Epidemiology, Air Pollution, Ambient Air Quality

Key words: lead exposure, aviation fuel, air pollution, mortality, cardiovascular

JEL codes: Q53, I18

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Cardiovascular Mortality and Leaded Aviation Fuel: Evidence from Piston-Engine Air Traffic in North Carolina[1]

Lead is a neurotoxin that damages multiple systems in the body. While neurodevelopmental effects in children are well documented, adults are also adversely affected by lead exposure (EPA 2013). Of particular concern is the increased risk of cardiovascular morbidity and mortality in adults (EPA 2013; Lamas et al. 2021).

Piston-engine aircraft operations using leaded fuel (termed aviation gasoline, or avgas) currently represent the largest source of airborne lead in the U.S., contributing 70% of lead emissions (EPA 2021a). While jet-engine aircraft (which do not use leaded fuel) dominate commercial air traffic, smaller piston-engine aircraft are widely used for non-commercial purposes that fall under the heading of general aviation, including commuting, recreation, flight instruction, and agriculture. There are roughly 13,000 airports nationwide, most of which include piston-engine airplane traffic (EPA 2020a).

The United States Environmental Protection Agency (EPA) estimates that over 5 million people live in Census blocks located within 500 meters of a runway at an airport with piston-engine aircraft (EPA 2020b). Previous studies have found an association between exposure to leaded aviation fuel and children's blood lead levels (BLLs) (Miranda et al., 2011; Zahran et al., 2017; Mountain Data Group, 2021). There is also a growing literature examining the association between lead exposure and adult cardiovascular mortality (Aoki et al. 2016, Lanphear et al. 2018, Menke et al. 2006, Ruiz-Hernandez et al. 2017). However, to our knowledge, no studies have examined how exposure to leaded aviation fuel emissions affects cardiovascular mortality.

We address this gap in the literature by estimating the effects of year-to-year changes in piston-engine and general aviation aircraft operations on cardiovascular mortality rates among older adults from 2000 to 2017 in North Carolina. Our study uses a quasi-experimental research design that examines the association between piston-engine operations and annual cardiovascular mortality rates among individuals age 65 and older living in Census block groups closer to airports (the "treated" group) and farther away from airports (the "control" group). We use coarsened exact matching (Iacus et al. 2012) to ensure that our treated and control groups are similar in terms of observable socioeconomic characteristics that could affect cardiovascular mortality. We address the potential for confounding of leaded fuel exposure from other health hazards at airports by controlling for different types of aircraft operations that do not emit lead but do generate noise and other pollutants such as particulate matter and volatile organic compounds associated with cardiovascular disease. We include block group

[1] The authors thank the Children's Environmental Health Initiative (CEHI) at the University of Notre Dame, including CEHI Director Marie Lynn Miranda and Claire Osgood, for their generosity in sharing the data and providing technical support; as well as Wes Austin, US EPA National Center for Environmental Economics; Adam Theising, US EPA Office of Pollution Prevention and Toxics; Juleen Lam, California State University, East Bay; Howard Chang, Emory University; Stephanie Deflorio-Barker, US EPA Office of Research and Development; and Kimberly Bertrand, Boston University School of Medicine; for their comments and suggestions. We also thank Brian Murphy and Doug Sage from the Federal Aviation Administration for providing access to historical FAA airport master records. The protocol for this study was approved by the University of Notre Dame Institutional Review Board. The views expressed in this paper are those of the authors and do not necessarily represent those of the U.S. EPA.

intercepts to control for unobserved determinants of cardiovascular mortality at the neighborhood level that remain stable over time.

This study finds a significant adverse association between piston-engine air traffic and cardiovascular mortality near single-runway airports. The magnitude of this association declines monotonically from 1 km to 4 km from airport runways. Our primary estimate suggests that a 10 percent reduction in piston-engine air traffic is associated with a 2 percent reduction in cardiovascular mortality for populations age 65 and older living within 2 km of an airport runway. If this reduction in piston-engine aircraft were offset by an equal increase in small jet or turbine flights that do not use leaded fuel, then the net effect within 2 km would be a 0.9 percent reduction in cardiovascular mortality. This 1.1 percent reduction may better isolate the effects of reduced lead exposure, because similarly sized small jet and turbine flights may present similar levels of noise and other pollutants that could contribute to mortality. We do not find consistent statistically significant adverse effects from changes in annual piston-engine operations near multi-runway airports, where there is greater uncertainty about which runways and block groups experienced exposures to leaded fuel emissions. Such spatial precision is important in contexts like this one, where the disamenity is very localized. The statistically significant adverse effects are also limited to Instrument Flight Rules (IFR) piston-engine flights, which are explicitly tracked by FAA computer systems. We do not find statistically significant effects for general aviation flights for which the FAA data are less reliable. The results suggest that (i) reducing lead emissions from aviation could yield substantial health benefits for adult populations, and (ii) more refined data are needed, particularly in terms of smaller general aviation flights and the intra-airport location of emissions.

Background on Leaded Aviation Gasoline

Tetraethyl lead is added to aviation gasoline to boost octane and prevent engine knock. Since the 1970s, piston-engine aircraft have predominantly used a grade of avgas called one hundred octane low lead (100LL) containing 2.12 grams of lead per gallon (NAS 2021). Alternatives with lower lead levels are not widely available, and unleaded fuels that meet the octane requirements for high-performance piston-engine aircraft have not yet been developed (NAS 2021). Piston-engine helicopters, which are not the focus of our study, also use leaded fuel.[2] In contrast, jets, military planes, and other turbine-engine aircraft use unleaded fuel.

Piston-engine aircraft lead emissions occur throughout the phases of a flight, including start-up, idling, taxiing, run-up, takeoff, cruising, and landing. Lead emissions are highly concentrated during ground-based run-up operations conducted prior to takeoff, next to the end of the runway, making this area the maximum impact site for lead air concentrations at airports (EPA 2020a). Releases also occur in maintenance and refueling areas. Piston-engine airplanes typically take off in the direction of the wind, so the maximum impact site can change with wind direction, particularly at airports with more than one runway.

[2] Piston-engine helicopters comprise two percent of the approximately 144,000 piston-engine aircraft currently active in the U.S. and account for four percent of hours flown (NAS 2021). EPA's (2020a) limited characterization of lead emissions from helicopters suggests that they generate lower air lead concentrations than fixed-wing airplanes, particularly during takeoff and landing.

EPA (2010) has discussed considerations in the determination of whether aircraft lead emissions endanger public health or welfare but has not yet issued a proposed determination evaluating endangerment. In 2008 and 2010, EPA established new monitoring requirements for sources emitting lead. As a result, state and local agencies were required to monitor lead at airports where emissions estimates exceeded one ton per year and at a subset of airports that met certain criteria (EPA 2015). The 3-month average lead concentrations at the airport monitors ranged from 0.01 to 0.33 $\mu g/m^3$, with the range in concentrations largely explained by monitor location relative to the end of the runway. Monitoring values exceeded the National Ambient Air Quality Standard (NAAQS) for lead of 0.15 $\mu g/m^3$ over a rolling 3-month average at two of the airports. In 2020, EPA (2020a) extrapolated air quality modeling results to estimate 3-month average lead concentrations at U.S. airports nationwide and found that they ranged from 0.0075 $\mu g/m^3$ to 0.475 $\mu g/m^3$ at the maximum impact site and up to 500 meters downwind. In most cases, values were not estimated to exceed the NAAQS. However, modeling showed that it is possible for levels to exceed the NAAQS at the maximum impact site at airports with relatively high numbers of piston-engine aircraft operations, particularly those with a higher proportion of multi-engine aircraft. In early 2022, EPA announced plans to issue a proposed endangerment finding.

Literature review

Previous studies have examined the effect of exposure to aviation fuel on children's blood lead levels. A study of six counties in North Carolina found higher BLLs among children living within 1.5 kilometers of airport boundaries after controlling for other lead exposure risk factors including socioeconomic status and housing age (Miranda et al. 2011). A study in Michigan found higher BLLs among children in Census tracts up to 3 kilometers from airports, and up to 4 kilometers from airports for which data on monthly aviation traffic were available from the Federal Aviation Administration (FAA) (Zahran et al. 2017). That study also found higher BLLs downwind of airports and during months with more piston-engine air traffic. In addition, Zahran et al. found a drop in BLLs corresponding to the grounding of air traffic after the Sept. 11, 2001, terrorist attacks. A recent report examining an airport in Santa Clara County, California, found higher children's BLLs closer to the airport, downwind of the airport, and in months with more piston-engine air traffic (Mountain Data Group 2021). Wolfe et al. (2016) did not conduct an empirical analysis of children's BLL, but instead used air quality modeling and existing statistical relationships between air lead concentrations, blood lead levels, and children's IQ to estimate the social costs of leaded avgas emissions. They estimated that aircraft-related emissions cause over $1 billion in losses annually due to cognitive damages that reduce children's lifetime earnings.

We are aware of only one peer-reviewed study examining occupational exposure to lead from avgas.[3] A study of aircraft maintenance workers in the Republic of Korea found significantly higher BLLs among maintenance crews at air bases where leaded avgas was used compared to air bases where jet fuel was used (Park et al. 2013). Workers' BLLs also increased with time spent near runways where avgas was used.

[3] A gray literature report on an investigation of potential lead exposures at an aircraft repair and flight school facility found that workers' BLLs did not exceed 10 micrograms per deciliter (the CDC "level of concern" at that time), nor did air lead levels exceed occupational exposure limits (Chen and Eisenberg 2013). The investigation did not assess whether worker BLLs were significantly higher than those of the general population of adults.

Empirical studies have also shown increases in air and soil lead levels near airports. Carr et al. (2011)'s study of Santa Monica Airport found air lead concentrations above background levels within 450 meters of the airport boundaries when averaging over a rolling 3-month period, and up to 900 meters downwind of the airport on individual days. A study of soil lead concentrations near three Oklahoma airports found elevated lead levels near refueling stations, runways, taxiways, and at downwind locations (McCumber and Strevett 2017). Higher soil lead levels were also found near the two single-runway airports, possibly because emissions may have been less dispersed than at the multi-runway airport.

The EPA's (2013) Integrated Science Assessment for Lead found robust evidence of a causal relationship between lead exposure and coronary heart disease and hypertension in adults. Lead affects cardiovascular function through multiple mechanisms, including increased oxidative stress, endothelial dysfunction, atherosclerosis, and hypertension, as well as decreased heart rate variability (Navas-Acien 2021). Several studies have shown a statistically significant relationship between adult BLLs and cardiovascular mortality in U.S. populations with mean BLLs < 5 µg/dL, while controlling for other risk factors including age, sex, race, body mass index, and smoking (Aoki et al. 2016, Lanphear et al. 2018, Menke et al. 2006, Ruiz-Hernandez et al. 2017). This literature has not examined the sources of lead exposure, though these cohorts were likely to have been exposed to high levels of ambient lead in air prior to the phaseout of lead in road gasoline.

EPA (2013) noted that there is uncertainty about the timing, frequency, and duration of lead exposure causing adverse cardiovascular effects. Because adult BLLs reflect a combination of recent lead exposure and past exposure due to endogenous release of lead stored in bone, the studies mentioned above did not disentangle the contributions of contemporaneous versus past exposures to adverse health effects. Recent evidence, however, suggests that reductions in adult lead exposure can lead to near-term improvements in cardiovascular outcomes. A national-level study of the 2007 voluntary phaseout of leaded gasoline in U.S. auto racing found an immediate decline in annual cardiovascular mortality among those age 65 and older in counties with a racetrack compared to counties without a racetrack (Hollingsworth and Rudik 2021). A clinical trial of chelation therapy to remove lead and other heavy metals from patients with severe cardiovascular morbidity caused rapid improvements in cardiovascular function (Navas-Acien 2021).

While we are unaware of existing research on the impact of leaded aviation fuel on cardiovascular health, several studies have examined the health effects of aviation noise and other pollutants. A study of 89 major U.S. airports found that hospitalization for cardiovascular disease was significantly associated with modeled zip-code aircraft noise (Correia et al. 2013). Studies in Europe have reported associations between aviation noise and adverse cardiovascular effects (Peters et al. 2018). A literature review found adverse health effects in occupationally exposed and residential populations near airports (Bendtsen et al. 2021). A study of residential populations within 10 km of California's 12 largest airports found a significant contemporaneous increase in respiratory and heart-related hospital admissions among those age 65 and older from aviation-related carbon monoxide exposure (Schlenker and Walker 2016). Elevated concentrations of fine and ultrafine particulates and other criteria pollutants have been found in residential areas and downwind areas up to several kilometers from major airports (Hudda et al. 2014; Hudda et al. 2020; Riley et al. 2021).

Studies have also examined whether populations living near airports have different sociodemographic characteristics than those living farther away. EPA's (2020b) analysis of populations living within 500 meters of airports nationwide found, on average, a higher proportion of White residents, a lower proportion of residents of color, and a slightly lower proportion of children eligible for free or reduced-price lunch near airports compared to the total U.S. population. However, a study of major airport hubs found larger increases in the proportions of residents of color and rental housing units near these airports over time compared to trends in their respective metropolitan regions (Woodburn 2017). A recent working paper on residential property markets near airports with piston-engine air traffic found that neighborhoods immediately downwind had lower median incomes and a higher proportion of Black residents than other neighborhoods near these airports (Theising 2021).[4] Thus, previous literature suggests that it is important to address potential confounding from other airport disamenities and to control for neighborhood sociodemographic trends to identify the effect of leaded aviation fuel on cardiovascular outcomes.

Data

We compiled a comprehensive statewide panel dataset of cardiovascular mortality rates among the population of individuals age 65 and older in North Carolina from 2000 to 2017. The unit of observation is each 2010 Census block group in each year. Mortality records from the North Carolina State Center for Health Statistics were obtained through an agreement with the Children's Environmental Health Initiative (CEHI) at the University of Notre Dame. The analysis was conducted the analysis according to a research protocol approved by the University of Notre Dame's Institutional Review Board. We used individual mortality records from North Carolina from 2000 to 2017 (N = 1,436,194). The mortality records included the individual's date of birth, date of death, residential address at the time of death, sex, race, and cause of death as indicated by ICD-10 codes. CEHI used residential address to geocode each record and spatially link it with the corresponding 2010 Census block group identifier. We dropped records for individuals not living in North Carolina at the time of death, records not matched to a Census block group, and duplicate records (134,003 observations). Because this study focuses on cardiovascular mortality among older adults, we further restricted the sample to individuals age 65 or older at the time of death with a disease of the circulatory system listed as the primary cause of death (ICD-10 codes I00-I99) (N = 321,445).[5]

The Federal Aviation Administration (FAA) provided data on location and aviation traffic for North Carolina airports from a variety of sources (Table 1). We obtained the geographic coordinates of airport runways from FAA Airport Master Records (also called 5010 forms).[6] These data indicate that there were

[4] That study did not find evidence that property prices changed in response to information disclosures about lead emissions at airports, except for temporary effects at two airports where lead levels exceeded the NAAQS.
[5] Our use of ICD-10 codes I00-I99 is consistent with analyses of the association between adult BLL and cardiovascular mortality by Menke et al. (2006), Aoki et al. (2016), and Lanphear et al. (2018). The most common causes of death were ischemic heart diseases (I20-I25), other forms of heart disease (I30-I52), and cerebrovascular diseases (I60-I69) (see Appendix Table A1).
[6] FAA does not make historic Airport Master Records available online but shared data for the years 1998 through 2019 at the authors' request. We obtained data for 2020 in October 2020 from https://www.faa.gov/airports/airport_safety/airportdata_5010/. Geographic coordinates correspond to the

over 400 airports operating in North Carolina during the study period, in addition to heliports and other aviation facilities. Airport Master Records also include data on the number of general aviation single- and multi-engine aircraft based at the airport and the number of operations (i.e., takeoffs or landings) of different flight user classes, including commercial air traffic (air carrier and air taxi), general aviation, and military. However, fewer than half of the airports report operations data, and those that do report are not required to update the data annually, so the operations data are not always current at the time of reporting.[7]

The FAA Traffic Flow Management System Count (TFMSC) and Air Traffic Activity Data System (ATADS) databases provide more detailed aviation traffic data but for fewer airports. TFMSC provides daily aircraft operations data by engine type for flights that use Instrument Flight Rules (IFR) and are recorded in FAA's computer system. These data include operations for approximately 2,000 of the largest airports in the United States. TFMSC excludes traffic that flies under Visual Flight Rules (VFR) and some low-altitude IFR traffic. The TFMSC database includes IFR flight records for 72 North Carolina airport locations.[8] The engine type data provided by TFMSC are particularly useful for our study because only piston-engine aircraft use leaded fuel. Zahran et al. (2017) and Mountain Data Group (2021) used TFMSC data in their analyses of children's blood lead levels, and Theising (2021) used these data in his property value study.

ATADS includes operations data for approximately 500 US airports with air traffic control towers. ATADS includes both IFR and VFR operations, making it a more comprehensive data source than TFMSC in terms of number of operations. However, it does not provide engine type; instead, it categorizes operations by user class (air carrier, air taxi, general aviation, and military).[9] EPA (2020a) estimated that roughly 70% of general aviation and 20% of air taxi operations use piston-engine aircraft and hence, leaded fuel. The ATADS data indicate that VFR flights comprise close to half of general aviation air traffic at these airports. ATADS only includes 11 North Carolina airports (all of which are also included in TFMSC). EPA (2020a) has used both ATADS and 5010 data to develop estimates of lead emissions and ambient air concentrations from piston-engine air traffic.

For each airport with TFMSC data, we obtained the number of IFR departures and arrivals at each airport for each calendar year during 2000-2017 by aircraft engine type (piston, jet, and turbine) and size (small equipment and all larger equipment types). Piston engine flights are of primary interest in our study because they use leaded aviation fuel. Jet and turbine aviation traffic do not use leaded fuel but are important to control for because they generate other pollutants, such as particular matter, volatile

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Airport Reference Point, a calculation based on the airport runway(s) geodetics (Doug Sage, pers. comm. Nov. 2020).

[7] Out of 435 North Carolina airports for which we have 5010 reports, only 178 reported general aviation operations. At 82 of these airports (46%), reported general aviation operations are the same in every year, suggesting that they may have never been updated. For 5010 forms from 2010 on, we have data on the 12-month period that the reported operations data represent. These data indicate that there is, on average, a 2-year lag between the year of the 5010 form and the year the operations data correspond to.

[8] One airport location in our study changed Location Identifiers (LocIDs) during the study period, so our TMFSC data include 73 unique LocIDs representing 72 airports.

[9] Air carrier and air taxi are both types of commercial operations, with air taxi operations using smaller planes and make shorter trips than air carrier. General aviation is defined as all civilian, non-commercial aviation activity.

organic compounds, and noise, that are associated with adverse cardiovascular morbidity and mortality (Bendtsen et al. 2021). Piston-engine aircraft in our sample are almost exclusively categorized as small equipment, jet aircraft are mostly larger sizes, and other turbine-engine aircraft are a mix of sizes.[10]

Table 1. FAA data sources for general aviation and/or piston-engine operations

Data source	Number of North Carolina airports included	Engine-type information available?	Includes Instrument Flight Rules (IFR) and Visual Flight Rules (VFR) operations?	Reporting frequency	Earliest date available
5010 forms	> 400 (but only 178 have non-missing operations data)	No	Yes (but not reported separately)	Annually for some airports, but often less frequent	1998
Traffic Flow Management System Counts (TFMSC)	72	Yes	No (IFR only)	Daily	2000
Air Traffic Activity Data System (ATADS)	11	No	Yes	Daily	1990

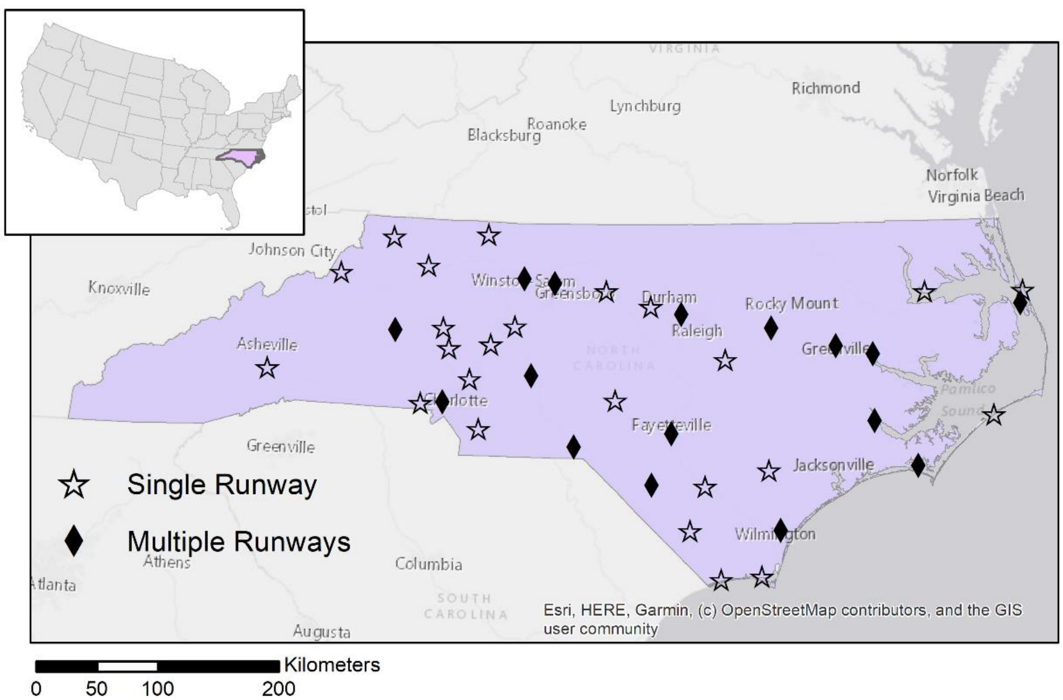
Although the data are not as detailed, we are also interested in the number of general aviation VFR operations at each airport in each year. Because most general aviation activity uses piston-engine aircraft, and most other flight types do not (EPA 2020a), we use general aviation operations reported by ATADS and 5010 forms as a proxy for piston-engine VFR operations. We obtained the number of annual general aviation VFR flights from ATADS data when available. When ATADS data were unavailable, we used information from the FAA 5010 forms on general aviation operations. The 5010 forms do not distinguish between IFR and VFR general aviation operations, so we subtract the number of piston-engine IFR operations indicated by TFMSC from the total number of general aviation operations reported by the 5010 forms to derive an estimate of general aviation VFR operations at these airports. Our data indicate that the number of general aviation IFR operations is highly correlated with the number of multi-engine piston aircraft based at airports, while the number of general aviation VFR operations is highly correlated with the number of single-engine piston aircraft based at airports. We exclude six airports from our analysis where TFMSC data are available, but for which the general aviation VFR operations data are missing from the 5010 reports.

[10] Weight classes in the TFMSC database included heavy, B757, large jet, large commuter, medium commuter, and small equipment. We pooled the first five categories together and refer to these equipment types as "large." For our study area and period, 99% of piston-engine operations, 1% of jet operations, and 34% of turbine-engine operations were categorized as small equipment.

We linked each 2010 Census block group in North Carolina to the closest TFMSC airport using geodesic distances calculated from each Census block centroid to the nearest runway at the airport.[11] We conducted all GIS analyses using ArcMap 10.8.1. The distances for each block were then aggregated to the block group level by taking a population-based weighted average. We also recorded the number of runways at each airport.

We focus our analysis on forty North Carolina airports that meet the following three criteria: 1) data on piston-engine IFR flight operations from TFMSC are available; 2) data on general aviation operations from ATADS or 5010 reports are available; and 3) there is at least one Census block group with a centroid located within 2 km of the airport runway(s). We focus on airports with populations within 2 km because past empirical research found effects on children's BLL to be concentrated within a few kilometers of airports. Twenty-four of the forty airports included in the analysis had a single runway, and 16 had between two and four runways (Figure 1). Figure 2 shows the trend in annual average piston-engine IFR operations at single-runway and multi-runway airports during the study period.

Figure 1. North Carolina airports with flight operations data available and populations located within 2 km



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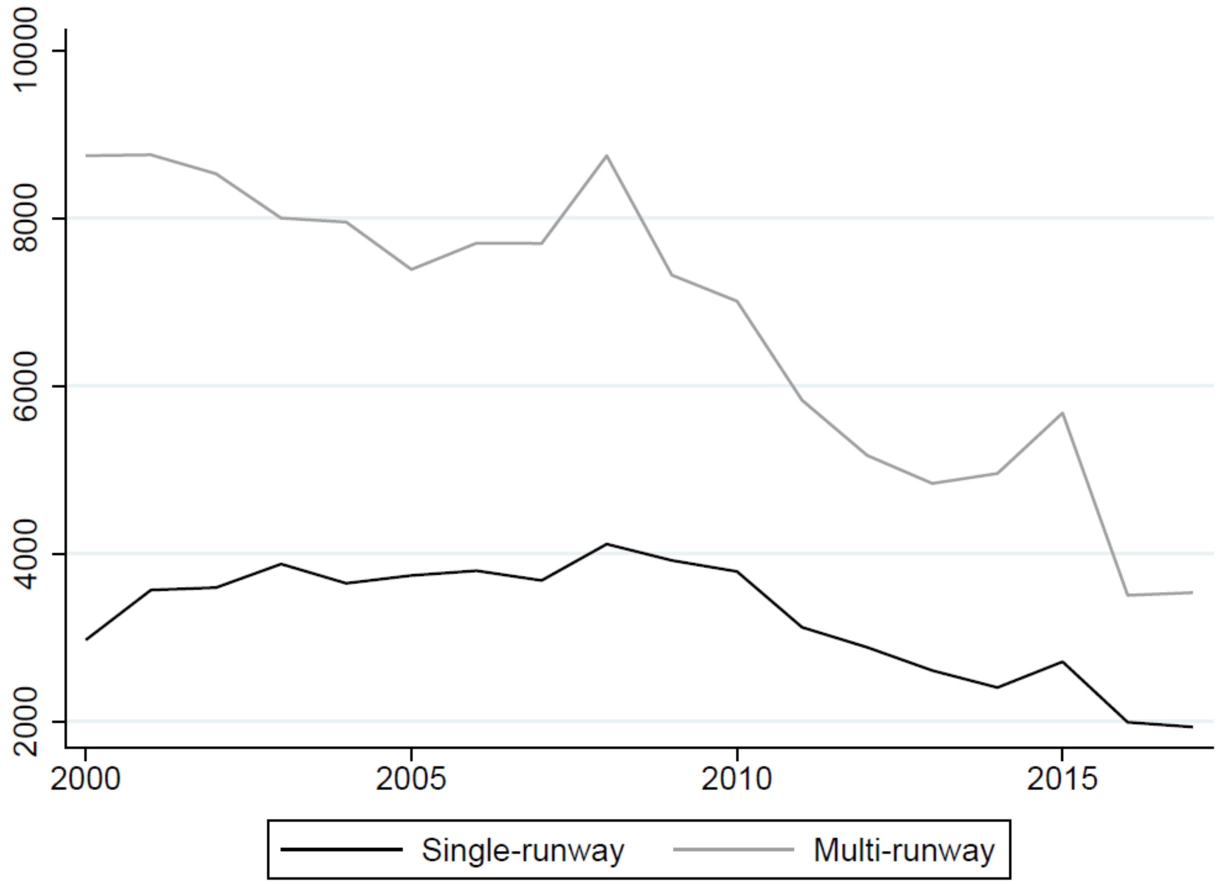
[11] A spatially explicit FAA data layer of the runway footprints was obtained from ESRI ArcGIS Online ("Runways", https://services6.arcgis.com/ssFJjBXIUyZDrSYZ/ArcGIS/rest/services/Runways/FeatureServer, accessed 16 July 2021).

Figure 2. Annual average piston-engine IFR operations at single-runway and multi-runway airports in North Carolina, 2000-2017



Note: Annual averages were calculated using CEM weights assuming a 2 km treatment group (explained in Econometric Analysis section).

Out of 6,155 2010 Census block groups in North Carolina, 1,764 fell within 10 km of one of the 40 airports shown in Figure 1. We focus our analysis on these block groups, which included 92,908 65-and-over cardiovascular deaths during the study period. While we hypothesize that any health effects from aviation fuel emissions are likely to be concentrated within a few kilometers of airport runways based on past literature (Miranda et al. 2011, Zahran et al. 2017), we include more distant block groups out to 10 km in the analysis as a less-exposed "control" group. No Census block groups in our study were within 4 km of more than one TFMSC airport, though 1% of block groups were within 10 km of more than one TFMSC airport.

We incorporated demographic and socioeconomic variables for each block group into the analysis using data from the 2000 and 2010 Decennial Censuses of Population and Housing and the 2019 American Community Survey (ACS) 5-year estimates downloaded from the IPUMS National Historical GIS Information System (NHGIS; Manson et al. 2021).[12] These variables include total population age 65 and

[12] Because ACS 2019 5-year estimates synthesize data from 2015 to 2019, we treat these estimates as representative of the 2017 midpoint year.

older, share of the population that is Black, share of the population that is Hispanic or Latino, share of housing stock that is vacant, share of occupied housing that is renter-occupied, median household income, share of the population age 25 and over with a college degree, and share of housing stock built before 1950. Pre-1950 housing stock is another potential source of lead exposure due to the widespread use of leaded paint and plumbing in older homes.[13] We also used data on total population and area of each block group to calculate population density. We linearly interpolated these variables from 2000 to 2010 and from 2010 to 2017 to obtain estimates for each year in our study.[14] We control for exposure to stationary industrial sources of lead and other air toxics using data from EPA's Risk-Screening Environmental Indicators (RSEI) model.[15] For each block group and year in our analysis, the RSEI geographic microdata provide lead air concentrations and aggregate toxicity-weighted concentrations of other pollutants attributable to emissions from stationary industrial sources that report to the Toxics Release Inventory.[16] Airport emissions are not included in the Toxics Release Inventory.

We linked each Census block group to non-TFMSC airports and heliports and roadways, which could also be sources of lead and other pollutants.[17] We also calculated distance to the nearest hospital, since access to medical care can affect whether mortality occurs after a myocardial infarction or other life-threatening emergency (Nicholl et al. 2007; Wei et al. 2008).[18] As with our measure of distances to airports, we calculated distances for each Census block and then aggregated up to the block group level by taking a population-based weighted average. We also constructed a measure of the percent of each block group exposed to over 55 decibels of transportation noise from roadways and aviation using the 2016 National Transportation Noise Map (Bureau of Transportation Statistics 2017).[19] We lack temporal variation in these variables, so their effects cannot be identified in our primary models that include block group intercepts, but we included them in a spatially coarser airport intercept model.

We included two additional county-level control variables that could affect cardiovascular mortality trends over time: the unemployment rate and exposure to heat waves, as measured by the number of

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[13] While the federal bans on residential lead paint and lead service lines did not go into effect until 1978 and 1986, respectively, these sources are more likely to be present in pre-1950 housing stock (Cornwell et al. 2016, Jacobs et al. 2002).

[14] IPUMS NHGIS provides integrated Census data over time for several variables, allowing us to include 2000 Census block group data in our analysis based on 2010 block group identifiers for all Census variables in our analysis except for median household income, percent of the adult population with a college degree, and share of housing stock built pre-1950. For these three variables, we imputed values for the years 2000-2009 using the predicted values from regressing each variable on year and the other Census variables in our analysis for 2010-2017.

[15] EPA Risk-Screening Environmental Indicators (RSEI) Model, https://www.epa.gov/rsei, accessed 19 Nov 2021.

[16] Because TRI reporting requirements changed for lead and several other chemicals in 2001, we do not use RSEI data for the year 2000 and instead make the simplifying assumption that concentrations in 2000 were equal to concentrations in 2001. The measure of aggregate toxicity-weighted air concentrations only includes chemicals whose reporting requirements have not changed since 2001.

[17] Non-TFMSC airport and heliport locations are represented by FAA Airport Reference Points. Roadway data came from the US Census Bureau's TIGER/Line files (https://www.census.gov/cgi-bin/geo/shapefiles/index.php, accessed 19 May 2020).

[18] The locations of hospitals in North Carolina were obtained from NCOneMap (https://www.nconemap.gov/datasets/nconemap::hospitals/about , accessed 22 Feb 2021).

[19] The 2016 National Transportation Noise Map provides modelled estimates of aviation noise at 18 of the 40 airport locations in our analysis, representing 69% of block groups in the study area.

days exceeding 90 degrees Fahrenheit (e.g., Åström,et al. 2011; Halliday 2014). We obtained annual unemployment rate data from the U.S. Bureau of Labor Statistics' Local Area Unemployment Statistics program. We used data on daily temperatures from the National Oceanic and Atmospheric Administration's Climate Data Search to construct our measure of days exceeding 90 degrees.[20]

Other studies of aircraft emissions included measures of wind direction in their analyses (e.g., Zahran et al. 2017; Carr et al. 2011; Walker and Schlenker 2016), but we do not do so in our analysis. We obtained data on wind direction at 63 North Carolina airports during 2000 to 2017 from Iowa State University's Iowa Environmental Mesonet. An examination of these data showed a bimodal pattern of prevailing winds at many North Carolina airports, with winds blowing from the southwest for part of the year, and then from the northeast for the other part of the year, making it difficult to identify areas that are consistently downwind of airport runways.

Econometric analysis

Our outcome variable is the number of cardiovascular deaths among individuals age 65 and older in each block group and year. Our key exposure variables are proximity to the closest TFMSC airport and the numbers of piston-engine and general aviation flight operations at the closest TFMSC airport during the corresponding year interacted with proximity to the airport.

We use a Poisson model to estimate the relationship between mortality and avgas exposure, adjusting for several other explanatory variables (see Table 2). Sixteen percent of the block group-year observations in our study have zero cardiovascular deaths among individuals 65 and older. A Poisson model is appropriate for count data censored at zero and yields consistent estimates when used with fixed effects (Cameron and Trivedi 1998; Wooldridge 1999).[21] Ordinary Least Squares is not appropriate for such data because it can predict negative and non-integer values. The Poisson regression model and the closely related negative binomial regression model have been used in previous studies of environmental risk factors and disease incidence (e.g., DeFlorio-Barker et al. 2021; VoPham et al. 2018). We use the natural log of the total population age 65 and older in each block group in each year as the offset variable. The inclusion of the population offset allows us to interpret our model as estimating the cardiovascular mortality *rate* among the population of interest.

We first estimate a model to examine the association between cardiovascular mortality and proximity to the closest TFMSC airport. The model includes several control variables to adjust for other risk factors besides leaded aviation fuel emissions. These include the sociodemographic variables discussed above, industrial stationary source emissions, and for 18 airports in our sample, a time-invariant measure of airport noise. While block group fixed effects would further control for time-invariant socioeconomic

[20] Temperature data were missing for seven counties in North Carolina. We imputed values for these counties by taking the mean across counties in the same climatic region in North Carolina. We used maps from the State Climate Office of North Carolina to define the three climatic regions (http://www.climatechange.nc.gov/Climate_Maps_NC.pdf).

[21] While the negative binomial regression model is sometimes used as an alternative to the Poisson regression model for modeling over-dispersed count data, it can yield inconsistent parameter estimates when used with panel count data (Guimarães 2008; Wooldridge 1999).

and geographic determinants of mortality, we do not include them in this model because they are perfectly collinear with the airport proximity variables, which are of primary interest. Because we do not use block group fixed effects, we interpret the coefficients of this model as correlations rather than causal effects.

The airport proximity model can be written as:

$$(1) \quad m_{icat} = exp(\ln(pop65_{it}) + \alpha_1 D_{ia} + X_{ict}\beta + Y_t + B_\alpha + \tau_\alpha t)$$

Here, m_{icat} represents the number of cardiovascular deaths in the 65 and older population in block group *i,* in county *c,* located closest to TFMSC airport *a,* during year *t*. We model m_{icat} as a function of several variables, including the offset term representing the natural log of the number of people age 65 and older in block group *i* in year *t* ($pop65_{it}$). The coefficient on the offset term is constrained to equal one. D_{ia} is an indicator variable denoting that the population-weighted centroid of block group *i* is within a given distance of airport *a*. Due to the uncertainty about the spatial extent of any adverse effects from aircraft operations on cardiovascular mortality, we estimate the model four separate times using different distances to reflect possible treatment groups: 0-1, 0-2, 0-3, and 0-4 kilometers. To further examine heterogeneity with respect to distance, we also estimate a single regression that includes mutually exclusive distance indicators from 1 to 4 kilometers in 1-kilometer increments: 0-1, 1-2, 2-3, and 3-4 kilometers. [22]

We include a vector of block group and county control variables (X_{ict}), including airport noise, proximity to major roads, unemployment, and time-varying block group socioeconomic characteristics. Year-specific intercepts for each year of the analysis (Y_t) are included to capture statewide trends over time. Separate intercepts denoting the closest TFMSC airport (B_a) capture time-invariant location-and airport-specific factors affecting mortality rates, albeit at a relatively coarse geographic resolution. We also include a linear time trend that is specific to each airport, represented by $\tau_\alpha t$ to capture more local trends over the study period. Coefficients to be estimated include α_1, the correlation between airport proximity and mortality, and β, the effects of other characteristics on mortality. These coefficients represent the percent increase in cardiovascular mortality from a one-unit change in the corresponding explanatory variable.

To examine the effect of year-to-year changes in air traffic on cardiovascular mortality near airports, we turn to a different specification that exploits temporal variation in the number of piston-engine and other flight operations. This model includes block group-specific intercept terms (B_i) to absorb time-invariant neighborhood characteristics affecting mortality at a much finer spatial resolution than the airport intercepts included in the airport proximity model. We do not include the airport noise or proximity variables in this specification because they are perfectly collinear with the block group intercepts. The higher resolution block group intercepts absorb at a more local scale all observed and unobserved time-invariant neighborhood characteristics that are correlated with cardiovascular mortality, including proximity to an airport (D_{ia}) and characteristics of that airport (B_α). We interact airport proximity with different types of annual flight operations, including piston-engine IFR operations

[22] In this model, D_{ia} in equation (1) is a vector of mutually exclusive indicators denoting incremental distance bins.

other general aviation operations that typically use leaded fuel. Our inclusion of small and large jet- and turbine-engine flights that do not use leaded fuel helps to control for temporal variation in aviation noise and non-leaded fuel emissions that could affect cardiovascular mortality.

The annual flight operations model can be written as:

$$(2) \quad m_{icat} = exp(\ln(pop65_{it}) + \gamma_1 PE_{iat} + \gamma_2 LG_{iat} + \gamma_3 SM_{iat} + \gamma_4 GA_{iat} + \delta_1 D_{ia} * PE_{iat} + \delta_2 D_{ia} * LG_{iat} + \delta_3 D_{ia} * SM_{iat} + \delta_4 D_{ia} * GA_{iat} + \beta X_{ict} + Y_t + B_i + \tau_\alpha t)$$

We include the numbers of piston-engine (PE_{iat}), large jet or turbine (LG_{iat}), and small jet or turbine (SM_{iat}) IFR aviation operations, and the number of general aviation VFR operations (GA_{iat}) at the closest airport *a* to block group *i* during year *t.* We interact these aviation variables with D_{ia}, the airport proximity indicator corresponding to block group *i*'s location. These interaction terms are our key explanatory variables representing possible exposure to leaded aviation fuel emissions near airports, given by $D_{ia}*PE_{iat}$ and $D_{ia}*GA_{iat}$. Therefore, δ_1 and δ_4 are the parameters of primary interest. They represent the percent change in cardiovascular mortality per piston-engine IFR operation and general aviation VFR operation at different distances from the airport. Like the airport proximity model, we estimate the flight operations model using four separate regressions with different distances in each regression (0-1, 0-2, 0-3, and 0-4 kilometers). We also estimate a regression including mutually exclusive distances from 1 to 4 kilometers (0-1, 1-2, 2-3, and 3-4 kilometers). [23]

We cluster the standard errors by closest airport in the airport proximity model and by block group in the annual flight operations model (equations (1) and (2), respectively) to address unobserved spatial correlation in cardiovascular mortality at the same resolution as the spatial intercept terms.

We separately estimate these models for block groups near single-runway and multi-runway airports. We disaggregate by number of runways because we anticipate that our measure of proximity to airport traffic is more precise for single-runway airports. For airports with more than one runway, we lack data to apportion flight operations to specific runways at each airport, creating greater dispersion of emissions across space and uncertainty about where the emissions occurred, and hence which block groups were more exposed to air traffic. This potential for classical measurement error in our measure of air traffic exposure at multi-runway airports could bias our estimates of the impact of aircraft operations on mortality towards the null.

To ensure that the "treated" block groups located within D_{ia} of a TFMSC airport are comparable in terms of socioeconomic characteristics that could affect cardiovascular mortality to the "control" block groups located farther away (but still within 10 km), our primary estimates use coarsened exact matching (CEM) (Iacus et al. 2012). CEM is a pre-processing algorithm that identifies observations in the treatment and control groups that match in terms of all explanatory variables selected by the analyst, after first coarsening the continuous variables into discrete categories. CEM also derives weights to balance the matched distributions of the observed socioeconomic characteristics across the treatment and control

[23] In this specification, D_{ia} in equation (2) is a vector of mutually exclusive indicators denoting incremental distance bins.

groups. All treatment observations that do not have an identical “match” in the control group (and vice versa) are assigned a weight of zero and dropped from the sample.

We match our treated and control samples using seven coarsened block group sociodemographic variables and three non-coarsened variables. The coarsened variables include median income, population density, share of the adult population that graduated from college, share of the population that is Black, share of population that is 65 and older, share of housing that is renter-occupied, and share of housing that was built before 1950. We divide median income into tertiles, and for all other coarsened variables we created three categories defined by equally spaced cut points. We matched on the 2010 values for all Census variables. The three variables used for an exact match are county, year, and closest airport. In balancing observable sociodemographic characteristics across the treatment and control groups, this strategy may also increase similarity in unobservable traits that are correlated with the observable characteristics.

We generate four sets of CEM weights corresponding to four possible cutoffs delineating the treatment and control groups already discussed: 1 km, 2 km, 3 km, and 4 km from the closest TFMSC airport. The appendix also presents regression results using the full, unweighted sample. While we find that the results are robust across the two approaches, the CEM estimates are preferred because they improve the balance in sociodemographic covariates across block groups closer versus farther from airports in our sample, as discussed in the Results section.

Our preferred approach combining panel data, block group-specific intercepts, and matching allows us to more credibly isolate the effect of piston-engine aviation on cardiovascular mortality based on year-to-year changes in air traffic. The airport proximity model (equation 1) is less able to isolate this effect because airport proximity could be correlated with socioeconomic or other local attributes affecting cardiovascular mortality. The flight operations model interacting distance from the airport with annual aviation operations (equation 2) is conceptually similar to a quasi-experimental difference-in-difference model, although the exposure variable representing number of flight operations varies continuously over time rather than changing discretely at one point in time.

Results

Our full sample includes 31,197 census block group-year observations.[24] Using CEM to focus our analysis on a more homogenous matched sample of treated and control block groups greatly reduces the sample size. Using a treatment definition of 2 kilometers, we keep 73% of treatment observations and 19% of control observations and are left with 7,134 observations. Since most of the “pruned” observations are in the control group, we retain most observations in the treatment group closest to each TFMSC airport. Therefore, CEM helps us to identify the most appropriate counterfactual set of block groups. Using a treatment definition of 1 km yields a much smaller matched sample of 826 observations, while treatment definitions of 3 km and 4 km yield larger matched samples of 10,444 and 14,620 observations, respectively.

[24] This sample excludes 709 block group-year observations estimated to have zero individuals 65 and older, 5 observations with zero housing units, and 3 observations with an estimated cardiovascular mortality rate greater than one.

Table 2. Summary statistics by airport type and distance from airport: CEM sample

	Single-runway airports		p-value of difference in means	Multi-runway airports		p-value of difference in means
	0-2 km	2-10 km		0-2 km	2-10 km	
Outcome variable						
65+ CVD mortality rate	0.012 (0.012)	0.013 (0.011)	0.045	0.017 (0.015)	0.016 (0.014)	0.10
Exposure variables						
Piston-engine IFR operations	2,374.16 (2,532.48)	2,306.98 (2,521.26)	0.53	4,502.57 (3,742.53)	4,711.79 (3,880.03)	0.16
Large jet/ turbine IFR operations	1,437.08 (3,960.14)	1,346.03 (3,903.90)	0.58	40,695.11 (115,464.40)	52,806.77 (133,902.20)	0.016
Small jet/ turbine IFR operations	729.64 (1,140.95)	680.82 (1,127.22)	0.31	2,489,77 (2,192.57)	2,657.46 (2,314.80)	0.059
General aviation VFR operations	24,811.77 (18,849.85)	24,926.54 (18,616.47)	0.88	23,946.29 (11,727.97)	23,638.67 (11,506.22)	0.49
Time-variant control variables						
65+ population	214.2 (137.29)	222.61 (159.17)	0.20	176.45 (114.16)	184.65 (119.94)	0.075
Share black population	0.085 (0.096)	0.074 (0.100)	0.015	0.41 (0.32)	0.40 (0.32)	0.25
Share Hispanic population	0.060 (0.062)	0.056 (0.062)	0.14	0.087 (0.11)	0.084 (0.10)	0.75
Population density	0.00037 (0.00036)	0.00042 (0.00043)	<0.01	0.00070 (0.00060)	0.00074 (0.00060)	0.073
Percent vacant housing	0.14 (0.17)	0.19 (0.22)	<0.01	0.13 (0.08)	0.14 (0.14)	0.12
Percent rental housing	0.24 (0.16)	0.27 (0.18)	<0.01	0.51 (0.23)	0.51 (0.24)	0.84
Percent pre-1950 housing	0.043 (0.050)	0.072 (0.075)	<0.01	0.16 (0.14)	0.13 (0.14)	<0.01
Median income (2010$)	67,868.04 (25,223.92)	68,009.15 (30,130.86)	0.91	39,498.44 (18,965.69)	41,809.03 (20,180.05)	<0.01
Percent of adults 25+ with college degree	0.31 (0.17)	0.30 (0.19)	0.58	0.17 (0.13)	0.18 (0.12)	0.11
Days above 90 degrees	33.18 (25.42)	32.87 (24.95)	0.77	41.00 (23.02)	41.40 (23.22)	0.66
Unemployment rate	6.62 (2.66)	6.63 (2.67)	0.96	6.95 (2.61)	6.95 (2.60)	0.98

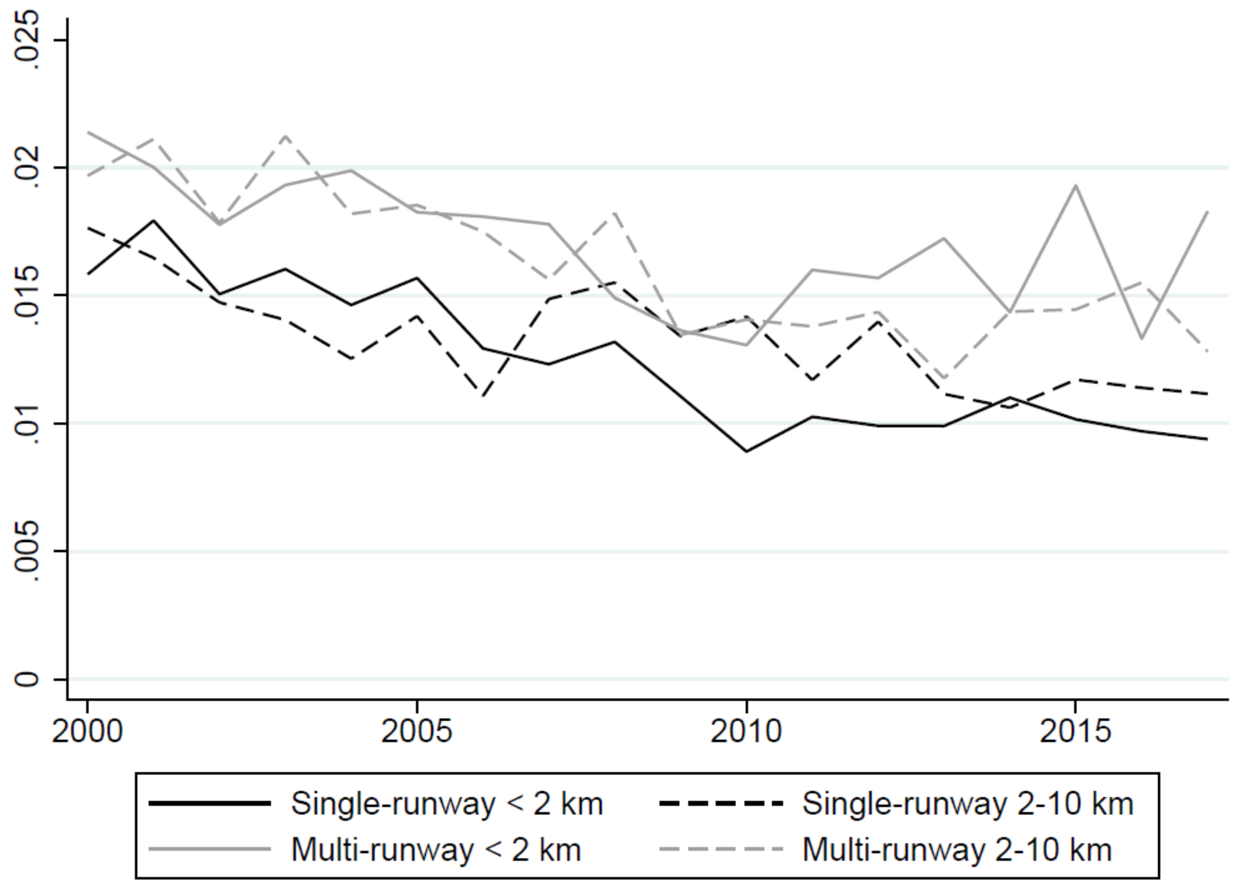
Toxicity-weighted lead air concentration	2.16 (3.21)	1.98 (3.19)	0.18	3.89 (7.73)	5.58 (12.49)	<0.01
Toxicity-weighted total air concentration of chemical releases	7,957.05 (44,881.71)	6,191.49 (38,227.35)	0.29	18,779.52 (73,898.80)	23,673.97 (136,759.50)	0.31
Charlotte Motor Speedway located within 4 km * pre-2007 lead phaseout	0.009 (0.095)	0.001 (0.038)	<0.01	0 (0)	0 (0)	-
Time-invariant variables (only included in airport intercepts models)						
Percent > 55 decibel transportation noise	4.90 (6.18)	3.09 (2.27)	<0.01	10.51 (11.97)	5.43 (6.74)	<0.01
Heliport located within 2 km	0.027 (0.16)	0.11 (0.31)	<0.01	0.059 (0.24)	0.11 (0.31)	<0.01
Major road located within 500 m	0.14 (0.34)	0.27 (0.45)	<0.01	0.35 (0.48)	0.42 (0.49)	<0.01
Major road located within 2 km	0.95 (0.22)	0.89 (0.31)	<0.01	0.96 (0.20)	0.97 (0.16)	0.059
Hospital located within 2 km	0.027 (0.16)	0.094 (0.29)	<0.01	0.079 (0.27)	0.13 (0.33)	<0.01
N	664	2,659		909	2,902	

Means calculated using CEM weights using 2 km treatment group. Standard deviations in parentheses.

Table 2 presents summary statistics for the CEM-weighted sample using the 2 km treatment definition. Appendix Table A2 presents summary statistics for all variables for the full sample, without matching. We present these statistics separately for single-runway and multi-runway airports. The matched treatment and control groups near single-runway airports have similarly high incomes and education levels, though the control group has somewhat higher rates of vacant, rental, and older housing, a lower percentage of Black residents, and a higher population density. Average air concentrations for lead and for aggregate toxicity-weighted emissions from stationary industrial sources were both similar across the treatment and control groups, though the control group includes more block groups located within 4 km of Charlotte Motor Speedway, a source of lead emissions before 2007.

The treatment and control groups near multi-runway airports have sociodemographic and housing characteristic that are similar to each other, though incomes are somewhat higher in the control group. Air lead concentrations from stationary industrial sources are also higher in the control group. The differences between the single-runway and multi-runway samples are more pronounced than the differences between the treatment and control groups for each airport type. Income and education levels are much higher, and the share of Black and Hispanic residents is much lower, near single-runway airports. These divergent demographic characteristics further support our decision to analyze single-runway and multi-runway airports separately.

Figure 3. Cardiovascular mortality rate (age 65 and older) by airport type and distance from airport: CEM sample



Annual averages calculated using CEM weights assuming a 2 km treatment group.

Figure 3 shows cardiovascular mortality rates near single- and multi-runway airports during the study period in the matched and weighted sample, again using the 2 km cutoff to define treatment and control groups near each airport type. The figure shows that cardiovascular mortality rates were somewhat lower near single-runway airports than multi-runway airports. Though there is substantial year-to-year variation, mortality rates were generally similar across the treatment and control groups near each airport type. Appendix Figure A1 shows trends for the full unweighted sample, revealing a larger divergence between the treatment and control groups for each airport type than the matched sample. This outcome suggests that CEM helped to identify treatment and control groups that are similar in terms of the broad determinants of cardiovascular mortality during the study period.

Table 3a presents the airport proximity coefficients from the regressions corresponding to equation (1) for the single- and multi-runway airport samples. We estimate four separate regressions, varying the cutoff between the treatment and control areas from 1 km to 4 km. The treatment definition used for deriving the CEM weights matches the distance variable included in each regression. We do not find a consistently adverse or monotonic relationship between cardiovascular mortality and proximity to single-runway TFMSC airports. Mortality rates are 13 percent higher within 4 km of these airports, but there is no statistically significant association using closer treatment definitions, which would be expected if exposure to leaded fuel at airports was the cause of elevated mortality. In contrast, cardiovascular mortality rates are higher closest to multi-runway airports. Mortality is 13 percent higher within both 1 km and 2 km of multi-runway airports, though the estimate is only statistically significant using the 0-2 km treatment definition. There is no significant association between mortality and proximity to multi-runway airports beyond this distance.

Table 3a. Key coefficient results from separate regressions with varying treatment cutoffs: Association between proximity to TFMSC airports with age 65+ cardiovascular mortality

	Single-runway airports	Multi-runway airports
0-1 km	-0.270	0.132
	(0.319)	(0.116)
Observations	380	446
Pseudo R2	0.157	0.0623
0-2 km	-0.0243	0.125**
	(0.0998)	(0.0577)
Observations	3,323	3,811
Pseudo R2	0.0963	0.0654
0-3 km	0.0442	-0.0150
	(0.0555)	(0.0489)
Observations	4,802	5,642
Pseudo R2	0.0973	0.0719
0-4km	0.126**	-0.0117
	(0.0540)	(0.0392)
Observations	7,104	7,516
Pseudo R2	0.0867	0.0743

All models use CEM weights (calculated using a treatment definition consistent with the treatment group for each regression) and include closest TFMSC airport fixed effects, year fixed effects, airport-year time trends, and time-variant and time-invariant control variables shown in Table 2. Robust standard errors clustered by closest airport are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3b presents the airport proximity coefficient estimates from a single regression model that includes mutually exclusive distance bins in 1-kilometer increments. This model uses the CEM sample and weights derived using the 4 km treatment group so that all of the distance bins included in the regression fall within this treatment group. The results are similar to those shown in Table 3a. There is no clear trend in the association between cardiovascular mortality and distance from either single-runway or multi-runway airports. There is a significantly higher cardiovascular mortality rate in block groups located between 3 and 4 km of single-runway airports. Because the models in Tables 3a and 3b do not include spatially refined block group intercepts, we cannot parse to what extent this adverse association is due to residual confounding with factors common to these neighborhoods or due to other lead and non-lead related hazards at these airports. (Appendix Table A3 shows the full set of coefficient estimates for all control variables included in this regression. Appendix Table A4 shows the key coefficient estimates for this model using the full sample, without CEM weights.)

Table 3b. Key coefficient results from single regression with 4 km treatment cutoff: Association between proximity to TFMSC airports with age 65+ cardiovascular mortality

	Single-runway airports	Multi-runway airports
0-1 km	-0.147	0.137
	(0.149)	(0.140)
1-2 km	0.0737	-0.0309
	(0.0775)	(0.0601)
2-3 km	0.119	-0.0711
	(0.103)	(0.0550)
3-4km	0.155***	0.0255
	(0.0553)	(0.0490)
Observations	7,104	7,516
Pseudo R2	0.0871	0.0748

This model uses CEM weights (calculated using the 4 km treatment group) and includes closest TFMSC airport fixed effects, year fixed effects, airport-year time trends, and time-variant and time-invariant control variables shown in Table 2. Robust standard errors clustered by closest airport are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 4a presents the key coefficients from the flight operations regressions (equation 2). This model is our preferred specification for estimating the unbiased effect of piston-engine air traffic on cardiovascular mortality. Similar to Table 3a, we present results from four different regressions in which the treatment definition (and corresponding CEM weights) varies from 1 to 4 km. The results indicate that piston-engine IFR flights have a statistically significant adverse effect on cardiovascular mortality for treatment groups that extend up to 4 km away from single-runway airports. The effect is largest within 1 km of the runway and declines monotonically as we expand the treatment group to include block groups farther from the nearest single-runway airport. The coefficient estimates indicate that each piston-engine flight operation at a single-runway airport increases cardiovascular mortality by 0.05 percent in the 0-1 km treatment group, 0.008 percent for the 0-2 km treatment group, and 0.005 percent for the 0-3 km treatment group. The effect is only marginally significant when using a 4 km treatment definition.

Table 4a. Key coefficient results from separate regressions with varying treatment cutoffs: Effect of annual flight operations on cardiovascular mortality near TFMSC airports

	Single-runway airports	Multi-runway airports
Piston-engine IFR operations*0-1 km	0.000506**	0.000242**
	(0.000247)	(0.000117)
Large jet/turbine IFR operations*0-1 km	0.000624	-2.93e-05
	(0.000555)	(0.000126)
Small jet/turbine IFR operations*0-1 km	-0.000393	2.50e-05
	(0.000515)	(0.000137)
General aviation VFR operations*0-1 km	-9.33e-06	1.25e-05
	(1.03e-05)	(1.18e-05)
Observations	380	446
Pseudo R2	0.187	0.0936
Piston-engine IFR operations*0-2 km	8.31e-05**	3.37e-06
	(3.84e-05)	(2.70e-05)
Large jet/turbine IFR operations*0-2 km	1.01e-05	-1.59e-06
	(5.87e-05)	(2.38e-06)
Small jet/turbine IFR operations*0-2 km	4.31e-05	9.11e-05*
	(8.20e-05)	(5.09e-05)
General aviation VFR operations*0-2 km	1.44e-06	-4.60e-06
	(3.36e-06)	(5.05e-06)
Observations	3,323	3,811
Pseudo R2	0.162	0.101
Piston-engine IFR operations*0-3 km	5.31e-05**	-9.50e-06
	(2.15e-05)	(1.92e-05)
Large jet/turbine IFR operations*0-3 km	4.51e-05	1.25e-06
	(4.38e-05)	(2.05e-06)
Small jet/turbine IFR operations*0-3 km	6.39e-05*	4.07e-05
	(3.39e-05)	(4.27e-05)
General aviation VFR operations*0-3 km	-3.65e-07	-1.41e-06
	(2.37e-06)	(3.80e-06)
Observations	4,802	5,642
Pseudo R2	0.162	0.115
Piston-engine IFR operations*0-4 km	3.77e-05*	-9.79e-06
	(2.04e-05)	(1.33e-05)
Large jet/turbine IFR operations*0-4 km	5.72e-05	2.04e-06
	(3.70e-05)	(2.03e-06)
Small jet/turbine IFR operations*0-4 km	4.57e-05*	1.71e-05
	(2.74e-05)	(3.19e-05)

General aviation VFR operations*0-4 km	6.80e-07	3.79e-06
	(2.08e-06)	(3.74e-06)
Observations	7,104	7,516
Pseudo R2	0.151	0.134

All models use CEM weights (calculated using a treatment definition consistent with the treatment group for each regression) and include block group fixed effects, year fixed effects, airport-year time trends, and all time-variant control variables shows in Table 2. Robust standard errors clustered by block group are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

We also find a significant increase in cardiovascular mortality of 0.02 percent per piston-engine IFR operation within 1 km of multi-runway airports, but find no significant effect from changes in piston-engine IFR operations beyond this localized area. As already noted, at multi-runway airports we have lower confidence that the distance between populations and airport runways is a good proxy for exposure to leaded fuel emissions because we do not know which runway was used for each operation.

Turning to the other flight types, the results suggest that general aviation VFR flights have no statistically significant effect on cardiovascular mortality in any of these regressions. This is not necessarily surprising considering that our VFR flight data lack accurate year-to-year variation at most airports given their exclusion from the TFMSC database. In addition, while most general aviation VFR flights are thought to be piston-engine, our data do not confirm engine type (and hence, the use of leaded fuel). Moreover, piston-engine IFR operations are more likely than VFR operations to be performed by twin engine aircraft, which have higher lead emissions per operation than single-engine aircraft.

The effects from small and large jet or turbine flights on cardiovascular mortality are also not significantly different from zero in most specifications. The exception is a marginally significant adverse effect of small jet and turbine operations on cardiovascular mortality within 0-3 and 0-4 km of single-runway airports. If these aircraft emit very fine particulates that disburse with wind, then adverse health effects could occur further from airports. The magnitude of the coefficients on small and large jet/turbine operations at single-runway airports is very similar to that of the piston-engine IFR coefficients using the 0-3 km and 0-4 km treatment definitions. These results suggest that piston-engine IFR flights are relatively more harmful to cardiovascular health than other flight types in areas located closest to single-runway airports, but that these effects may converge or even reverse a few kilometers away from the airports. We also find a marginally significant adverse effect of small jet or turbine flights within 0-2 km of multi-runway airports.

Table 4b presents results of the flight operations model using a single regression that interacts flight operations with mutually exclusive distance bins of 0-1, 1-2, 2-3, and 3-4 km from the closest airport. Consistent with the results in Table 4a, we find statistically significant effects of piston-engine operations in block groups with centroids 0-1 and 1-2 km from single-runway airports. Each piston-engine IFR flight operation increases cardiovascular mortality by 0.08 percent and 0.01 percent at these distances, respectively. The effects of piston-engine IFR operations are smaller and not statistically different from zero in the 2-3 and 3-4 km bins. This result suggests that the significant effects within 0-3 and 0-4 km shown in Table 4a were likely driven by the inclusion of block groups within 0-2 km of single-runway airports in the treatment area definitions in those models.

Table 4b. Key coefficient results from single regression with 4 km treatment cutoff: Effect of annual flight operations on cardiovascular mortality near TFMSC airports

	Single-runway airports	Multi-runway airports
Piston-engine IFR operations*0-1 km	0.000756**	3.99e-06
	(0.000323)	(7.19e-05)
Large jet/turbine IFR operations*0-1 km	0.000409*	0.000170
	(0.000230)	(0.000149)
Small jet/turbine IFR operations*0-1 km	-0.000487	-3.65e-07
	(0.000450)	(0.000187)
General aviation VFR operations*0-1 km	4.37e-06	-5.80e-06
	(3.13e-06)	(7.15e-06)
Piston-engine IFR operations*1-2 km	0.000117**	-7.55e-06
	(4.73e-05)	(2.43e-05)
Large jet/turbine IFR operations*1-2 km	5.85e-05	4.59e-07
	(5.80e-05)	(2.42e-06)
Small jet/turbine IFR operations*1-2 km	9.43e-05	0.000109*
	(8.55e-05)	(6.27e-05)
General aviation VFR operations*1-2 km	2.63e-07	5.25e-06
	(3.27e-06)	(4.98e-06)
Piston-engine IFR operations*2-3 km	3.82e-05	-3.29e-05*
	(2.32e-05)	(1.83e-05)
Large jet/turbine IFR operations*2-3 km	5.73e-05	2.69e-06
	(6.15e-05)	(2.45e-06)
Small jet/turbine IFR operations*2-3 km	5.76e-05*	-1.91e-05
	(3.43e-05)	(5.13e-05)
General aviation VFR operations*2-3 km	-4.63e-07	2.33e-06
	(2.42e-06)	(6.04e-06)
Piston-engine IFR operations*3-4 km	2.05e-05	-2.02e-06
	(2.58e-05)	(1.49e-05)
Large jet/turbine IFR operations*3-4 km	5.26e-05	1.73e-06
	(4.41e-05)	(2.47e-06)
Small jet/turbine IFR operations*3-4 km	2.67e-05	-4.75e-06
	(3.87e-05)	(3.93e-05)
General aviation VFR operations*3-4 km	1.39e-06	4.27e-06
	(3.75e-06)	(4.97e-06)
Observations	7,104	7,516
Pseudo R2	0.152	0.134

This models uses CEM weights (calculated using the 4 km treatment group) and includes block group fixed effects, year fixed effects, airport-year time trends, and all time-variant control variables shows in Table 2. Robust standard errors clustered by block group are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

In contrast to Table 4a, the estimated effect of piston-engine IFR operations within 1 km of multi-runway airports is smaller and not statistically different from zero. The main difference between these models is the treatment and control group definitions used to calculate the CEM sample and weights. The small number of block group-year observations within 1 km of the closest airport contributes to our uncertainty about the effect of air traffic operations near multi-runway airports.

The estimates of the effects of other flight types on cardiovascular mortality from Table 4b are generally similar to those from Table 4a. None are statistically significant at a 5% level in any of the distance buffers.

Appendix Table A5 presents the full set of coefficients for all explanatory variables for the CEM-weighted flight operations model corresponding to Table 4b. These results suggest that annual increases in cardiovascular mortality are significantly associated with decreases in the share of Hispanic residents, decreases in median income, decreased population density, and more days exceeding 90 degrees in communities near single- or multi-runway airports.

The primary finding that piston-engine IFR operations have a statistically significant adverse association with cardiovascular mortality within 0-1 and 1-2 km from single-runway airports is robust to alternative specifications that use the full sample without CEM weights, and to models that exclude other operation types.[25]

We provide an illustrative example of the magnitude of the adverse effect of piston-engine aircraft on cardiovascular mortality by calculating the impact of a 10 percent reduction in operations near single-runway airports. Using the coefficients for the 0-2 km treatment effect from column 1 of Table 4a, we estimate that reducing piston-engine IFR operations at single-runway airports by 10 percent, which is equivalent to 237 takeoffs or landings per airport on average, would result in a statistically significant 2 percent reduction in annual cardiovascular mortality among individuals age 65 and older, assuming that all other flight traffic is held constant. This equates to a drop in cardiovascular deaths of 0.047 per block group, which totals to about 2.5 avoided deaths per year across all block groups located within 2 km of one of the 24 single-runway airports in North Carolina. If we instead assume that the reduction in piston-engine IFR flights is balanced by an equal increase in the number of small jet or turbine IFR operations (which do not use leaded fuel), we obtain a net reduction in cardiovascular mortality of 0.9 percent, equivalent to 1.3 deaths per year across all block groups located within 2 km of a single-runway airport.[26] The latter illustration is of interest because it better isolates the effects associated with leaded

[25] Appendix Table A6 presents regression results using the full sample without CEM weights. These results are similar to the CEM-weighted model results shown in Table 4b, but the piston-engine IFR coefficients are slightly larger in the CEM-weighted model, suggesting that estimating the model using unmatched treatment and control groups with divergent socioeconomic characteristics leads to a potential downward bias in the coefficient estimates. As shown in Appendix Table A7, the piston-engine IFR operation coefficient estimates are similar to those in Table 4b when all other operation types except for piston-engine IFR traffic are excluded. This suggests that the primary results are not being driven by collinearity with the other flight operation variables.

[26] This net effect when assuming an offsetting increase in small jet or turbine IFR operations is not significantly different from zero ($p = 0.58$).

fuel emissions. Small jet and turbine IFR flights do not use leaded fuel but may emit similar levels of other pollutants and noise that could contribute to cardiovascular mortality.

Discussion

Our analysis indicates that increases in annual piston-engine air traffic are associated with significant increases in cardiovascular mortality among adults age 65 and older living near single-runway airports. However, our data has several limitations that may bias our estimates toward zero, suggesting that our estimates are conservative.

Unfortunately, we do not have blood lead surveillance data for adults or monitored air lead concentration data that would provide us with a more precise measure of lead exposure from piston-engine air traffic. Our reliance on airport proximity and aircraft operations as a less precise measure of exposure to lead emissions could lead to downward bias in our estimates.

Our measure of general aviation VFR flights is particularly coarse as an indicator of lead exposure. Our data source for VFR general aviation flights does not distinguish between piston- and non-piston-engine aircraft, though EPA (2020a) has noted that most of these flights are piston-engine. VFR flight data are not updated annually for most airports in our sample, reducing the temporal variation that we rely on for identification in our preferred regression models. These limitations could contribute to our lack of precise estimates of the association between general aviation VFR flights and cardiovascular mortality. Given the lack of precision in our measure of piston-engine VFR flights, we cannot conclude from our null results that these flights have no effect on cardiovascular mortality. VFR flights are more numerous than piston-engine IFR flights, so they remain an important source of lead emissions.

Because leaded fuel usage can vary across parts of an airport, there is also uncertainty about the specific location of the lead emissions, leading to classical measurement error. This source of measurement error should be less pronounced for single-runway airports. Our use of population-weighted block group centroids instead of individual residential addresses as an indicator of population location exacerbates this source of measurement error, further biasing our results toward the null. However, our finding of more pronounced adverse effects near single-runway airport is consistent with McCumber and Strevett's (2017) finding of higher soil lead levels near single-runway airports in their analysis of three airports in Oklahoma.

Our analysis focuses on the effects of year-to-year fluctuations in piston-engine air traffic. A key uncertainty in the scientific literature is the timing and duration of lead exposure resulting in adverse cardiovascular effects (EPA 2013). If cardiovascular damage accrues over many years of exposure, which is likely the case, our results underestimate the total contribution of piston-engine air traffic to cardiovascular mortality.

Our study is also limited to airports large enough to report data on piston-engine IFR flights to FAA, as reflected in the TFMSC database. We cannot assume that estimates of the impact of aviation traffic at larger airports is generalizable to smaller airports, which are likely to have fewer based aircraft and flight operations. Some of these smaller airports could be located closer to residential neighborhoods than larger airports if local zoning does not require setbacks, so lead emissions from these airports could still raise public health concerns. We did not conduct an analysis of proximity to smaller airports as a proxy for exposure because airport location could be correlated with socioeconomic and other determinants of cardiovascular mortality, making it challenging to isolate the effect of piston-engine air traffic holding all other risk factors constant with this approach.

As already noted, there is potential for omitted variable bias if neighborhoods near airports are systematically different from those farther away. We use several strategies to minimize this potential bias, particularly in the flight operations regressions. These strategies include spatially refined Census block group intercepts, coarsened exact matching on several socioeconomic characteristics that are associated with cardiovascular mortality rates, and the inclusion of numerous time-variant control variables and linear airport-specific time trends. To minimize bias due to confounding of aircraft lead emissions with aircraft noise and other pollutants that can cause cardiovascular damage, we adjust for aviation noise in our airport proximity regressions and account for large and small jet- and turbine-engine operations in our flight operations models. Despite this multi-pronged approach, we cannot assert with 100% confidence that we eliminated all sources of bias.

Given the potential for our results to be biased towards the null, it is notable that we estimate statistically significant increases in annual cardiovascular mortality from an increase in piston-engine IFR air traffic for block groups within 2 km of single-runway airports. The magnitude of this effect is similar to findings from other studies examining associations between airport pollution and cardiovascular disease. For example, Schlenker and Walker (2016) found that a one standard deviation increase in aircraft carbon monoxide emissions caused a 9 percent increase in daily mean hospital admissions for heart problems near California airports. This result corresponds to a 1.4 percent increase in hospital admissions per 10 percent increase in carbon monoxide. Correia et al. (2013) found that hospitalization for cardiovascular disease was 3.5% higher in zip codes with 10 dB higher 90^{th} centile aviation noise exposure. This finding roughly translates to a 1.8 percent increase in cardiovascular disease per 10 percent increase in 90^{th} centile aviation noise. However, our findings are only applicable to a highly localized area near single-runway airports, whereas these studies found effects surrounding broader geographic areas near major airports.

Conclusions

Piston-engine aviation is the largest remaining source of airborne lead emissions in the United States. Our study is the first to estimate the effect of piston-engine aircraft operations on cardiovascular mortality. We find that adults age 65 and older living within two kilometers of single-runway airports have higher cardiovascular mortality rates in years with more piston-engine IFR operations compared to adults living farther away from these airports. We do not consistently find that cardiovascular morality is significantly higher in years with more piston-engine IFR operations at multi-runway airports, nor do we find higher mortality in years with more general aviation VFR operations, possibly because our measure of leaded avgas exposure is less precise in these cases.

To obtain more reliable and precise estimates of the effect of leaded aviation fuel emissions on cardiovascular outcomes, a direction for future research is to conduct similar analyses using a larger sample of airports with reliable flight operations data. Data on the variation in air lead concentrations and/or adult blood lead levels over time near airports would further expand opportunities to identify the health effects of changes in adult lead exposure. In addition, a more comprehensive dataset of individual-level health and location data for the entire population of adults age 65 and older living near airports—not just those who experience a fatality or other significant adverse effect—would allow for a more spatially refined analysis based on the distance from individuals' residences to the closest airport runway. In the meantime, our study presents preliminary evidence that reducing emissions from leaded aviation fuel could have significant health benefits for adult populations who are often overlooked in discussions of lead exposure.

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Appendix

Figure A1. Cardiovascular mortality rate (age 65 and older) by airport type and distance from airport: Full sample

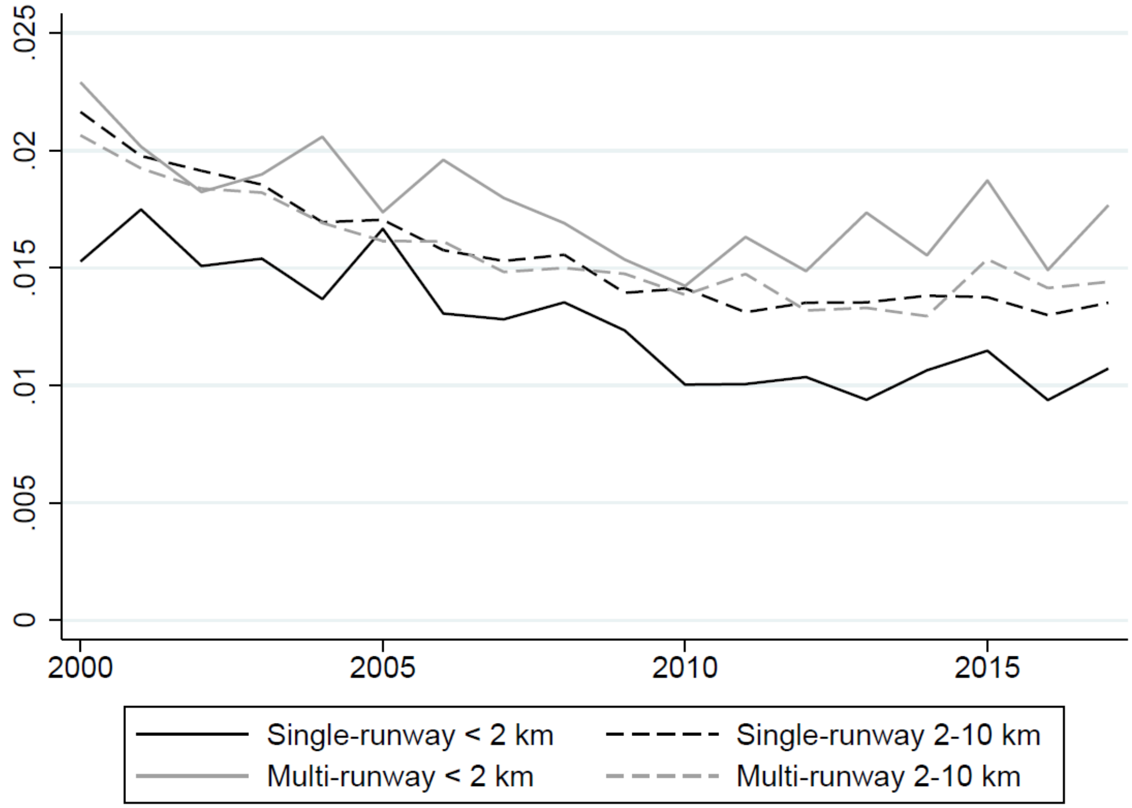

Table A1. Appendix table: ICD-10 codes for cardiovascular deaths among individuals age 65 and older in North Carolina, 2000-2017

	Number of deaths	Percentage of deaths
I00-I02– acute rheumatic fever	6	<1%
I05-I09 – chronic rheumatic heart diseases	1,161	<1%
I10-I15 – hypertensive diseases	19,694	6%
I20-I25 – ischemic heart diseases	144,190	45%
I26-I28 – pulmonary heart disease and diseases of pulmonary circulation	5,978	2%
I30-I52 – other forms of heart disease	69,462	22%
I60-I69 – cerebrovascular diseases	67,499	21%
I70-I79 – diseases of arteries, arterioles and capillaries	12,171	4%
I80-I89 – diseases of veins, lymphatic vessels and lymph nodes, not elsewhere classified	1,042	<1%
I95-I99 – other and unspecified disorders of the circulatory system	259	<1%
Total I00-I99 – diseases of the circulatory system	321,445	100%

Table A2. Summary statistics by airport type and distance from airport: full sample

	Single-runway airports		p-value of difference in means	Multi-runway airports		p-value of difference in means
	0-2 km	2-10 km		0-2 km	2-10 km	
Outcome variable						
Number of 65+ CVD deaths	2.55 (2.79)	3.16 (3.39)	<0.01	3.09 (3.41)	2.85 (3.18)	0.011
Exposure variables						
Piston-engine IFR operations	2,602.14 (2,940.56)	3,287.11 (3,528.17)	<0.01	4,170.90 (3,608.60)	6,921.76 (5,865.58)	<0.01
Large jet/ turbine IFR operations	2,112.27 (5,484.15)	2,552.21 (5,089.20)	0.011	39,918.12 (115,986.50)	113,453.40 (178,755.60)	<0.01
Small jet/ turbine IFR operations	845.15 (1,337.19)	1,229.35 (1,629.59)	<0.01	2,317.14 (2,184.43)	3,840.27 (2,894.09)	<0.01
General aviation VFR operations	26,011.13 (19,390.86)	28,644.00 (17,647.35)	<0.01	24,053.28 (11,526.59)	20,839.80 (10,756.56)	<0.01
Time-variant control variables						
65+ population	207.44 (139.16)	209.88 (149.18)	0.62	176.64 (104.80)	191.74 (136.60)	<0.01
Share black population	0.088 (0.096)	0.18 (0.19)	<0.01	0.42 (0.31)	0.27 (0.26)	<0.01
Share Hispanic population	0.063 (0.066)	0.078 (0.084)	<0.01	0.084 (0.11)	0.074 (0.094)	<0.01
Population density	0.00042 (0.00059)	0.00050 (0.00053)	<0.01	0.00065 (0.00059)	0.00084 (0.00070)	<0.01
Percent vacant housing	0.19 (0.20)	0.13 (0.13)	<0.01	0.13 (0.08)	0.10 (0.09)	<0.01
Percent rental housing	0.30 (0.20)	0.33 (0.22)	<0.01	0.48 (0.22)	0.41 (0.25)	<0.01
Percent pre-1950 housing	0.051 (0.065)	0.12 (0.14)	<0.01	0.16 (0.15)	0.13 (0.17)	<0.01
Median income (2010$)	62,576.34 (23,963.21)	58,625.32 (30,021.59)	<0.01	39,781.36 (17,908.55)	5,9707.25 (32,498.18)	<0.01
Percent of adults 25+ with college degree	0.29 (0.16)	0.24 (0.17)	<0.01	0.17 (0.12)	0.29 (0.19)	<0.01
Days above 90 degrees	33.95 (24.83)	34.67 (25.05)	0.39	41.01 (22.58)	42.41 (22.00)	0.034
Unemployment rate	6.68 (2.65)	6.74 (2.62)	<0.01	6.93 (2.56)	6.66 (2.49)	<0.01
Toxicity-weighted lead	1.82 (2.93)	3.04 (8.67)	<0.01	3.81 (7.34)	5.94 (29.51)	0.013

air concentration						
Toxicity-weighted total air concentration of chemical releases	6,093.79 (37,767.60)	10,196.27 (57,053.85)	0.030	18,620.90 (76,619.06)	32,529.24 (177,235.90)	<0.01
Charlotte Motor Speedway located within 4 km * pre-2007 lead phaseout	0.006 (0.080)	0.004 (0.061)		0 (0)	0 (0)	0.21
Time-invariant variables (only included in airport fixed effects models)						
Percent > 55 decibel transportation noise	5.24 (6.17)	3.42 (2.90)	<0.01	9.15 (11.09)	5.17 (7.67)	<0.01
Heliport located within 2 km	0.038 (0.19)	0.068 (0.25)	<0.01	0.045 (0.21)	0.13 (0.33)	<0.01
Major road located within 500 m	0.21 (0.40)	0.30 (0.46)	<0.01	(0.37) (0.48)	0.34 (0.47)	0.032
Major road located within 2 km	0.96 (0.19)	0.85 (0.36)	<0.01	0.95 (0.21)	0.92 (0.27)	<0.01
Hospital located within 2 km	0.054 (0.23)	0.10 (0.30)	<0.01	0.090 (0.29)	0.16 (0.37)	<0.01
N	944	12,662		1,198	16,393	

Standard deviations in parentheses

Table A3. Full coefficient results using single regression with a 4 km treatment cutoff: Association of airport proximity and cardiovascular mortality near TFMSC airports using CEM sample

	Single-runway airports	Multi-runway airports
Located 0-1 km of TFMSC airport	-0.147	0.137
	(0.149)	(0.140)
Located 1-2 km of TFMSC airport	0.0737	-0.0309
	(0.0775)	(0.0601)
Located 2-3 km of TFMSC airport	0.119	-0.0711
	(0.103)	(0.0550)
Located 3-4 km of TFMSC airport	0.155***	0.0255
	(0.0553)	(0.0490)
Share Black population	0.133	-0.216*
	(0.217)	(0.114)
Share Hispanic population	-0.0953	-0.532
	(0.253)	(0.330)
Population density	-22.38	-2.299
	(73.82)	(61.54)
Share vacant housing	0.251	0.115
	(0.161)	(0.252)
Share rental housing	0.348***	0.296
	(0.0990)	(0.241)
Median income	-2.70e-06*	-5.07e-06***
	(1.59e-06)	(1.68e-06)
Share college graduates	-0.481**	0.0434
	(0.215)	(0.259)
Share pre-1950 housing	0.249	0.565***
	(0.290)	(0.181)
Days above 90 degrees	0.00287*	-0.000165
	(0.00161)	(0.00147)
Unemployment rate	0.0105	0.00469
	(0.0165)	(0.0150)
Toxicity-weighted lead air concentration	-0.00248	0.000409
	(0.00233)	(0.000316)
Toxicity-weighted total air concentration	4.40e-09	-8.89e-09
of chemical releases	(1.71e-07)	(4.13e-08)
Percent > 55 decibel transportation noise	-0.00744	0.00450***
Heliport located within 2 km	(0.00913)	(0.00108)
Percent > 55 decibel transportation noise	0.163	0.0310
	(0.135)	(0.131)
Major road located within 2 km	0.157**	-0.0849
	(0.0610)	(0.0580)
Major road located within 500 m	0.0341	-0.0538
	(0.0713)	(0.0364)
Hospital located within 2 km	-0.0446	0.159
	(0.131)	(0.102)
Charlotte Motor Speedway located within	-0.0395	-

4 km	(0.0481)	
Charlotte Motor Speedway located within	-0.218***	-
4 km*pre-2007 lead phaseout	(0.0244)	
General aviation VFR data missing		-0.130**
		(0.0564)
Constant	-3.836***	-3.627***
	(0.192)	(0.148)
Observations	7,104	7,516
Pseudo R	0.0871	0.0748

This model uses CEM weights derived based on a 4 km treatment cutoff and includes airport fixed effects, year fixed effects, and airport-year time trends. Robust standard errors clustered by closest airport are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A4. Key coefficient results from single regression model with a 4 km treatment cutoff: Impact of airport proximity on cardiovascular mortality within near TFMSC airports using **full sample without matching**

	Single-runway airports	Multi-runway airports
0-1 km	-0.396***	0.0593
	(0.105)	(0.0712)
1-2 km	-0.0669	0.0434
	(0.0557)	(0.0715)
2-3 km	0.0222	-0.00306
	(0.0683)	(0.0656)
3-4km	0.0583	0.0110
	(0.0458)	(0.0344)
Observations	13,606	17,591
Pseudo R2	0.0949	0.0621

This model includes closest TFMSC airport fixed effects, year fixed effects, airport-year time trends, and control variables shown in Table 2. Robust standard errors clustered by closest airport are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A5. Full coefficient results using single regression model with a 4 km treatment cutoff: Impact of annual flight operations on cardiovascular mortality near TFMSC airports using CEM sample

	Single-runway airports	Multi-runway airports
Piston-engine IFR operations*0-1 km	0.000756**	3.99e-06
	(0.000323)	(7.19e-05)
Large jet/turbine IFR operations*0-1 km	0.000409*	0.000170
	(0.000230)	(0.000149)
Small jet/turbine IFR operations*0-1 km	-0.000487	-3.65e-07
	(0.000450)	(0.000187)
General aviation VFR operations*0-1 km	4.37e-06	-5.80e-06
	(3.13e-06)	(7.15e-06)
Piston-engine IFR operations*1-2 km	0.000117**	-7.55e-06
	(4.73e-05)	(2.43e-05)
Large jet/turbine IFR operations*1-2 km	5.85e-05	4.59e-07
	(5.80e-05)	(2.42e-06)
Small jet/turbine IFR operations*1-2 km	9.43e-05	0.000109*
	(8.55e-05)	(6.27e-05)
General aviation VFR operations*1-2 km	2.63e-07	5.25e-06
	(3.27e-06)	(4.98e-06)
Piston-engine IFR operations*2-3 km	3.82e-05	-3.29e-05*
	(2.32e-05)	(1.83e-05)
Large jet/turbine IFR operations*2-3 km	5.73e-05	2.69e-06
	(6.15e-05)	(2.45e-06)
Small jet/turbine IFR operations*2-3 km	5.76e-05*	-1.91e-05
	(3.43e-05)	(5.13e-05)
General aviation VFR operations*2-3 km	-4.63e-07	2.33e-06
	(2.42e-06)	(6.04e-06)
Piston-engine IFR operations*3-4 km	2.05e-05	-2.02e-06
	(2.58e-05)	(1.49e-05)
Large jet/turbine IFR operations *3-4 km	5.26e-05	1.73e-06
	(4.41e-05)	(2.47e-06)
Small jet/turbine IFR operations*3-4 km	2.67e-05	-4.75e-06
	(3.87e-05)	(3.93e-05)
General aviation VFR operations*3-4 km	1.39e-06	4.27e-06
	(3.75e-06)	(4.97e-06)
Piston-engine IFR operations at closest airport	-1.43e-05	2.73e-05
	(1.82e-05)	(1.75e-05)
Large jet/turbine IFR operations at closest airport	-1.35e-05	-1.75e-06
	(2.99e-05)	(1.34e-06)
Small jet/turbine IFR operations at closest airport	6.54e-06	9.18e-06
	(3.31e-05)	(2.54e-05)
General aviation VFR operations at closest airport	-1.76e-06	-2.55e-06
	(1.85e-06)	(4.43e-06)
Share Black population	0.273	-0.0272
	(0.398)	(0.345)
Share Hispanic population	-0.930**	-0.0688

	(0.365)	(0.641)
Population density	-134.3	-246.5*
	(363.1)	(134.7)
Share vacant housing	0.287	0.474
	(0.418)	(0.498)
Share rental housing	0.210	0.284
	(0.324)	(0.432)
Median income	-2.07e-06	-7.52e-06**
	(1.77e-06)	(3.07e-06)
Share college graduates	0.317	0.0105
	(0.358)	(0.426)
Share pre-1950 housing	-0.293	-0.981
	(0.446)	(0.635)
Days above 90 degrees	0.00201*	-0.000225
	(0.00108)	(0.00184)
Unemployment rate	0.0233	0.0103
	(0.0184)	(0.0209)
Toxicity-weighted lead air concentration	-0.000649	0.000419
	(0.00216)	(0.000534)
Toxicity-weighted total air concentration of chemical releases	1.44e-07	4.64e-08
	(1.63e-07)	(7.40e-08)
Charlotte Motor Speedway located within 4 km* pre-2007 lead phaseout	-0.403	
	(0.268)	
General aviation VFR data missing		-0.152
		(0.148)
Constant	-4.098***	-2.539***
	(0.443)	(0.278)
Observations	7,104	7,516
Pseudo R2	0.152	0.134

This model uses CEM weights (derived based on a 4 km treatment cutoff) and includes block group fixed effects, year fixed effects, and airport-year time trends. Robust standard errors clustered by block group are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table A6. Key coefficient results from single regression model: Impact of annual flight operations on cardiovascular mortality near TFMSC airports using **full sample without matching**

	Single-runway airports	Multi-runway airports
Piston-engine IFR operations*0-1 km	0.000485**	-2.08e-05
	(0.000199)	(0.000111)
Large jet/turbine IFR operations*0-1 km	0.000335*	3.15e-05
	(0.000180)	(8.73e-05)
Small jet/turbine IFR operations*0-1 km	5.39e-07	0.000188
	(0.000466)	(0.000122)
General aviation VFR operations*0-1 km	9.46e-07	-9.01e-06
	(1.96e-06)	(6.60e-06)
Piston-engine IFR operations*1-2 km	9.75e-05***	-2.81e-05
	(3.58e-05)	(2.14e-05)
Large jet/turbine IFR operations*1-2 km	2.25e-05	-9.67e-07
	(3.65e-05)	(1.93e-06)
Small jet/turbine IFR operations*1-2 km	4.68e-05	5.48e-05
	(6.25e-05)	(4.63e-05)
General aviation VFR operations*1-2 km	1.42e-07	2.59e-06
	(2.82e-06)	(3.94e-06)
Piston-engine IFR operations*2-3 km	3.39e-05	-1.21e-05
	(2.11e-05)	(2.62e-05)
Large jet/turbine IFR operations*2-3 km	3.42e-05	8.67e-07
	(5.20e-05)	(3.30e-06)
Small jet/turbine IFR operations*2-3 km	6.73e-05*	3.40e-05
	(3.55e-05)	(5.23e-05)
General aviation VFR operations*2-3 km	-1.82e-06	-3.63e-06
	(1.70e-06)	(5.01e-06)
Piston-engine IFR operations*3-4 km	2.45e-05	9.42e-06
	(2.21e-05)	(8.94e-06)
Large jet/turbine IFR operations*3-4 km	1.80e-05	1.51e-06
	(2.52e-05)	(2.12e-06)
Small jet/turbine IFR operations*3-4 km	2.39e-05	-5.32e-06
	(3.90e-05)	(3.21e-05)
General aviation VFR operations*3-4 km	4.04e-07	2.49e-06
	(3.16e-06)	(3.66e-06)
Observations	13,606	17,591
Pseudo R2	0.168	0.145

This model includes block group fixed effects, year fixed effects, airport-year time trends, and all time-variant control variables shows in Table 2. Robust standard errors clustered by block group in parentheses.

Table A7: Key coefficient results using single regression model with a 4 km treatment cutoff: Impact of **only piston-engine** annual flight operations on cardiovascular mortality near TFMSC airports

	Single-runway airports	Multi-runway airports
Piston-engine IFR operations*0-1 km	0.000800**	1.52e-05
	(0.000382)	(9.09e-05)
Piston-engine IFR operations*1-2 km	0.000117***	-4.31e-06
	(4.03e-05)	(1.97e-05)
Piston-engine IFR operations*2-3 km	3.21e-05	-4.11e-05**
	(2.09e-05)	(2.04e-05)
Piston-engine IFR operations*3-4 km	2.34e-05	-5.13e-06
	(2.36e-05)	(1.67e-05)
Observations	7,104	7,516
Pseudo R2	0.151	0.134

This model uses CEM weights (derived based on a 4 km treatment cutoff) and includes block group fixed effects, year fixed effects, and airport-year time trends. Robust standard errors clustered by block group are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1