The Effect of Leaded Aviation Gasoline on Blood Lead in Children

Sammy Zahran, Terrence Iverson, Shawn P. McElmurry, Stephan Weiler

Abstract: Lead is a neurotoxin with developmentally harmful effects in children. In the United States, over half the current flow of lead into the atmosphere is attributable to lead-formulated aviation gasoline (avgas), used in a large fraction of piston-engine aircraft. Various public interest firms have petitioned the EPA to find endangerment from and regulate lead emitted by piston-engine aircraft, though the EPA has so far ruled against such petitions. To address an EPA request for more evidence, we construct a novel data set that links time and spatially referenced blood lead data from over a million children to 448 nearby airports in Michigan. Across a series of tests, and adjusting for other known sources of lead exposure, we find that child blood lead levels (1) increase dose-responsively in proximity to airports, (2) decline measurably among children sampled in the months after 9/11, (3) increase dose-responsively in the flow of piston-engine aircraft traffic, (4) increase in the percentage of prevailing wind days drifting in the direction of a child's residential location, and (5) behave intuitively and significantly when considering two-way and three-way interactions of our main treatment variables. To quantify the policy relevance of the results we provide a conservative estimate of the social damages attributable to avgas consumption. Damages are at least $10 per gallon, which can be compared to a pump price of about $6 per gallon.

JEL Codes: I120, I180, J130, Q510, Q530

Keywords: Aviation gasoline, Blood lead levels, Child health, Lead exposure

CHILDREN EXPOSED TO LEAD have diminished life chances. Studies link lead exposure to adverse mental and behavioral outcomes, such as IQ loss, poor academic achievement, attention-deficit disorders, delinquency, and violence and to irreversible physical

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health problems such as hypertensive disorders, damage to renal and cardiovascular systems, and tooth decay.[1] While lead has been banned in the United States from the largest original sources—paint, plumbing, food cans, and automobile gasoline—deposition associated with lead-formulated aviation gasoline (avgas) from piston engine aircraft (PEA) remains an important source of new emissions. The flow of lead from PEA constitutes between half and two-thirds of remaining lead emissions in the United States (EPA 2008). Advocacy groups have petitioned the Environmental Protection Agency (EPA) to find endangerment from these emissions, but the agency has so far declined, holding that additional studies are needed "to differentiate aircraft lead emissions from other sources of ambient air lead" (EPA 2010a, 2).

While some studies have linked avgas use to elevated atmospheric lead levels in the vicinity of airports (Piazza 1999; Tetra Tech 2007; Callahan 2010; EPA 2010b; Carr et al. 2011), to date only one study has linked airport proximity to blood lead levels (BLL) in children. Miranda et al. (2011) find a significant correlation between child BLL and proximity to airport facilities in six counties in North Carolina. While this spatial correlation is highly suggestive, to more conclusively link lead in avgas to child BLL, we need to disentangle the flow of lead due to aviation-related sources from other exposure pathways that potentially increase in airport proximity.

A common exposure pathway for children in the United States is dust associated with deteriorating or haphazardly removed lead-based paint. Exposure to lead-based paint is primarily a problem in old houses, particularly in homes built before 1950. In our study area, the percentage of homes built prior to 1950 is almost twice as high in neighborhoods proximate to an airport compared to those more distant.[2] Moreover, due to zoning restrictions, lead-emitting industrial facilities are more common in the vicinity of airports. Of the 400+ census tracts within 2 kilometers of an airport in Michigan, 41% also have a lead-emitting facility within 2 kilometers. Failure to account for the spatial coincidence of older homes and point-source polluters could inflate estimated health risks from avgas exposure. We address this spatial coincidence problem by including neighborhood measures of *housing stock age* and *location of industrial point sources*, among other relevant controls.

In addition to accounting for alternative exposure pathways, airport proximity (in itself) is an incomplete measure of avgas exposure risk. First, airports vary immensely

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1. Needleman and Gastonis (1990), Dietrich et al. (2001), Canfield et al. (2003), Nevin (2006), Miranda et al. (2007), Reyes (2007), Jusko et al. (2008), Zahran et al. (2009), Nigg et al. (2010), Mielke and Zahran (2012), Reyes (2012).

2. The percentage is 44% for neighborhoods ≤2 kilometers of an airport compared to 23% for neighborhoods 9–10 kilometers from an airport.

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in PEA traffic. In our sample, the average monthly number of PEA operations varies from 7 (at MTC Selfridge) to 1,099 (at PTK Pontiac). Neglecting the volume of PEA traffic amounts to assuming that all airports traffic equally in PEA. Second, the fate and transport of avgas emissions depend on the direction of prevailing winds that vary in and across airport facilities. Insofar as avgas is an independent source of lead exposure, two children equidistant to the same airport face different risk of elevated blood lead depending on the child's residential near angle to the nearest airport. We address these important sources of omitted variable bias in previous literature by including measures of prevailing wind direction and PEA traffic.

Despite more extensive controls and improvements in the operationalization of exposure risk, variation in child BLL near airports may pick up more than locational differences in lead deposition from PEA aircraft. First, a residential selection bias may operate if families residing near airports are less prone to undertake defensive actions, including measures to protect against alternative exposure pathways like lead-contaminated dust. In Michigan, populations of lower socioeconomic status are more likely to reside near airports. Compared to more distant neighborhoods (9–10 km), neighborhoods within 2 km of an airport have significantly higher percentages of households receiving public assistance (4.35 vs. 8.41, $t = 3.57$) and lower levels of educational attainment among adults ($\geq$ high school education, 81.45 vs. 75.98, $t = -2.03$). In addition to controlling for these and other measures of neighborhood socioeconomic status in regression models, our measure of prevailing wind direction provides an exogenous source of variation with respect to the problem of residential selection. In Michigan, prevailing wind direction is statistically unrelated to neighborhood socioeconomic composition at $\leq$2 km of an airport.[3] That is, disadvantaged populations proximate to airports are equally likely to be up versus downwind.

Second, an underappreciated source of child lead exposure is lead-concentrated soils, primarily due to legacy deposition from lead-formulated automobile gasoline. Urban geochemists have linked child BLL to the accumulation of lead in neighborhood soils. Contaminated soils enter a child's body through ingestion (involving hand-to-mouth behaviors) or inhalation of lead-concentrated soils resuspended during summer months (Filippelli et al. 2005; Laidlaw et al. 2005, 2012; Zahran et al. 2010, 2011, 2013). Both aircraft traffic and the atmospheric resuspension of contaminated soils peak in summer and retreat in winter (Laidlaw et al. 2012; Zahran et al. 2013).[4] Failure to account for this seasonal coincidence of avgas deposition and resuspension of legacy sources could upwardly bias the evaluation of avgas risk. To address this specific

3. The correlations between downwind risk (measured as the percentage days where wind drifts in the direction of a neighborhood) and percentage receiving public assistance ($p = .62$), median home value ($p = .32$), and percentage with $\geq$ high school education ($p = .29$) are indistinguishable from chance.

4. In our sample, PEA departures and arrivals are significantly higher ($t = -6.43$, $p < .01$) in the summer (428 per month) than in the winter (286 per month).

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problem, our research design exploits two independent sources of exogenous variation in lead deposition from piston engine aircraft traffic. First, we use an exogenous lead-deposition shock that resulted from the grounding and restriction of PEA traffic following the tragic events of September 11, 2001. Reflecting the drop in traffic, avgas sales in Michigan declined over 50% the month after September 11, 2001. Second, we use monthly data on PEA arrivals and departures by airport to test whether child BLL is dose-responsive in the volume of PEA traffic. This exploits spatial and temporal variation in PEA traffic driven by local meteorological conditions that are plausibly exogenous from other exposure pathways.

The analysis deploys a novel data set that includes BLL records for over a million children linked spatially and temporally to 448 fully operational airports across Michigan, and emissions data for all toxic release inventory facilities that emit lead. In addition, for a subset of airports, we also observe the monthly count of piston-engine aircraft operations. Across all tests rendered, we find consistent evidence that avgas use is significantly linked to elevated BLL in children near airports. Child BLL and the odds of eclipsing various CDC thresholds for concern (1) increase in proximity to airports, (2) decline in the months after September 11 among children proximate to airports, (3) increase in the flow of PEA traffic, (4) increase in the percentage of downwind days, and (5) behave intuitively with respect to two-way and three-way interactions of the main treatment variables.

To quantify the social cost of avgas exposure, we deploy a standard syllogism linking BLL to IQ loss, and IQ loss to future earnings (Schwartz 1994; Grosse et al. 2002; Gould 2009). We find that reducing PEA traffic in Michigan from the 50th percentile (407 monthly operations) to the 10th percentile (133 operations) would generate a social benefit, measured in terms of the net present value of future earnings, of about \$120 million. This translates to a bit over \$10 in external social cost per gallon of avgas sold, which can be compared to a pump price of about \$6 per gallon.[5] This estimate may be regarded as conservative because we consider only deposition near airports on a subset of the population (children under five), and we only account for the impact of IQ loss on earnings, one of several known damage channels.[6]

1. BACKGROUND: RATIONALE FOR AVGAS USE AND REGULATORY RESPONSE

Despite recent national interest in lead exposure following the preventable failure of the water distribution system in Flint, Michigan, lead pollution in the United States

5. Self-service price retrieved for Coleman Young Airport in Detroit, September 1, 2014.

6. In addition to IQ loss, lead exposure can cause growth stunting, seizures, and lasting damage to various body systems. Kemper, Bordley, and Downs (1998) provide comprehensive health care cost estimates from medical interventions necessary to treat both low and high level exposure to lead. Others have estimated the total direct costs of lead-linked crime, including victim costs, criminal justice processing, and incarceration, as well as lost earnings to victims and perpetrators of crime (Gould 2009).

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has evolved for the most part into a legacy problem. BLLs have declined dramatically in time (Raymond, Wheeler, and Brown 2014), and the most important exposure pathways for children nationwide involving legacy sources of lead-based paint and contaminated soils (Farfel et al. 2003; Zahran et al. 2010). Nevertheless, for the approximately 16 million people—and 3 million children—who live within a kilometer of airport facilities that service piston-engine aircraft, the continuing flow of lead into the environment remains a potentially serious source of exposure risk.

About 160,000 piston-engine aircraft are registered in the United States, constituting about 70% of the US air fleet. In 2011, these aircraft consumed an estimated 225 million gallons of avgas (Kessler 2013). This consumption implies a flow into the environment of about a million pounds of lead each year. While small compared to the amount consumed historically in automobile gasoline, the impact is spatially concentrated with approximately half of the lead from avgas depositing near airports (EPA 2008).

The primary rationale for the continued use of lead in avgas is aircraft safety. When engines are run at high power, as they always are in aircraft, there is a risk of preignition under compression—also known as "knocking." This damages the engine and can lead to sudden engine failure. Tetraethyl lead is one of the best-known additives for avoiding dangerous knocking (Ells 2006). The high intensity at which aircraft engines operate, together with the high stakes of engine failure, explain why tetraethyl lead is still used as an additive in avgas even though it has been banned from all other transportation fuels. Nevertheless, approximately three-quarters of the existing piston-engine fleet could transition safely to lead (and ethanol) free automotive gasoline at negligible additional costs (Kessler 2013). These planes continue to use leaded avgas in large part because it is the primary fuel available at many US airports.

In 2006 (and again in 2014 and joined by Physicians for Social Responsibility and Oregon Aviation Watch), the environmental group Friends of the Earth petitioned the EPA to find endangerment from and regulate lead emitted by piston-engine aircraft (EPA 2014). While both the EPA and the CDC have recognized that there is no known safe level of lead exposure (CDC 2012a, 2012b; DHHS 2012), the EPA ruled against the petition, calling for more studies to substantiate the risks. In 2013, the Federal Aviation Administration (FAA) announced the formation of the Piston Aviation Fuel Initiative, a joint effort between the FAA and industry partners, with the expressed goal of finding an unleaded replacement fuel that could be used as a drop-in substitute for the entire general aviation fleet by 2018 (FAA 2012). The findings below explicitly address the EPAs request for information. Our results lend credence to the concern of advocacy groups and add impetus to the FAA's ongoing effort to find a substitute fuel.

2. MATERIALS AND METHODS

2.1. Response Variables

Blood lead data were obtained by confidentiality agreement from the Michigan Department of Community Health (MDCH). The data set contains blood samples from

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1,043,391 fully observed children collected from January 2001 through December 2009 under the Healthy Homes and Lead Poisoning Prevention (HHLPP) program. HHLPP is funded by the CDC and enlists health providers across the state. The program is intended to support lead poisoning prevention and surveillance services for children in Michigan. Blood lead samples are collected during regular visits to a doctor with a sampling emphasis on at-risk children residing in older homes or neighborhoods known to have children with elevated blood lead levels. The total number of blood lead samples collected under the program represents about one-sixteenth of all children under 72 months of age in Michigan.

Blood lead data are reported in units of micrograms per deciliter of blood (μg/dL). The MDCH data also contain information on the census tract residential location of each child, the month and year of sample collection, child age in years (0–5), and child sex (male = 1, female = 0). As with previous research (Zahran et al. 2011), we analyze child BLL as a binary variable ($\geq 5\mu$g/dL = 1, $< 5\mu$g/dL = 0, and $\geq 10\mu$g/dL = 1, $< 10\mu$g/dL = 0). Two reasons motivate our decision to use threshold response variables instead of a continuous measure of blood lead. First, our thresholds of $\geq$5 and $\geq$10 μg/dL correspond to the CDCs present and past reference levels of elevated blood lead. Children with BLLs exceeding these "levels of concern" require case management. Second, 40.2% of children sampled have BLLs that are at or below test detection limits. Technically, the precise amount of lead in the bloodstream of a sampled child at or below detection limit is unknown. We can, however, determine with certainty whether or not a child's BLL is $\geq$5 or $\geq$10 μg/dL.[7]

2.2. Avgas Exposure Variables: Distance, Traffic, and Wind

Point location data on airports in Michigan were gathered from the Geographic Names Information System (GNIS). A total of 448 airports satisfied our inclusion criterion of having at least one child (with a BLL reading) residing within 10 km. Distance is measured in kilometers from the population-weighted centroid of each census tract where a child resides to the nearest GNIS airport. Distance to a hazardous land use is a standard proxy for exposure risk (see Rau, Urzua, and Reyes 2015). Following Miranda et al. (2011), we use distance data to test whether child BLLs are dose-responsive in distance to GNIS airports. For tests involving distance to the nearest GNIS airport, the sample size of fully observed children is 1,023,672.

We also collected data from the Federal Aviation Administration's Operations and Performance (FAAOP) system on the monthly sum of piston-engine aircraft depar-

7. To demonstrate the robustness of our findings (with respect to sign/significance), we also report statistical results with child BLLs measured continuously but caution about the potential for error-in-measurement given the noted test detection problem in the data. In models with BLL treated continuously, BLL is log transformed to address positive skew (S = 5.70) and severe kurtosis (K = 91.15). By taking the natural log of BLL, we eliminate skewness (S = 0.57) and substantially minimize kurtosis (K = 2.84).

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tures, arrivals, and aircraft seat count. A total of 27 airports are inventoried in the FAAOP system in Michigan from 2001 to 2009. The month of blood draw is linked to the corresponding month of PEA traffic at the nearest FAAOP airport, and we test whether child BLLs are dose-responsive in the volume of piston-engine aircraft traffic. Our use of current month without lags is motivated by the following considerations. Estimates of the half-life for lead in blood vary from as low as 15 days (Manton et al. 2000) to a more typical range of 21–30 days (Rabinowitz 1991; Lidsky and Schneider 2003). We explored several possible operations for lead exposure risk, including current month PEA traffic, prior month, and two months prior, as well as 2- and 3-month rolling averages. Of these, current month is the best predictor of elevated blood lead risk. Relatedly, figure 2, panel A, of the results section demonstrates a striking concurrent correlation between monthly PEA traffic and average BLLs in children. While it would be tempting to use several such measures in the econometric analysis, doing so would invite multicollinearity due to significant serial correlation in monthly PEA traffic across airports. In tests involving the use of distance to the nearest FAAOP airport, the sample size of fully observed children decreases to 364,292, corresponding to the reduction from 448 GNIS airports to 27 FAAOP airports.

In addition to airport proximity and the volume of PEA traffic, child exposure risk is also influenced by local wind patterns. To account for this, we collect prevailing wind direction distribution data at each FAAOP airport (from www.windfinder.com). To illustrate, figure 1 presents a compass plot of prevailing winds at DET, Coleman Young Municipal Airport in Detroit, Michigan. With near angle information linking a child's census tract location to the nearest FAAOP airport, we estimate downwind risk as the percentage of wind days that drift in the direction of the compass octant of a child's residential location. In addition to providing more valid operationalization of exposure risk, prevailing wind direction provides an exogenous source of variation with respect to the residential selection.

2.3. Control Variables

The econometric models control for a variety of other sources of lead exposure. Data from the Toxic Release Inventory (TRI) system identify 578 facilities that emitted lead or lead compounds in Michigan between 2001 and 2009. We measure the distance from the population-weighted centroid of each census tract to these lead-emitting facilities. TRI data allow us to test whether the count of point source polluters within 2 km of a child's residential neighborhood increases their likelihood of exceeding various CDC thresholds for concern.[8]

8. We calculated various distance buffers (0.5 km, 1 km, 1.5 km, etc.) and determined through both statistical analysis (in terms of predictive efficacy) and prior research (in terms of emissions dispersion) that a 2 km buffer was optimal.

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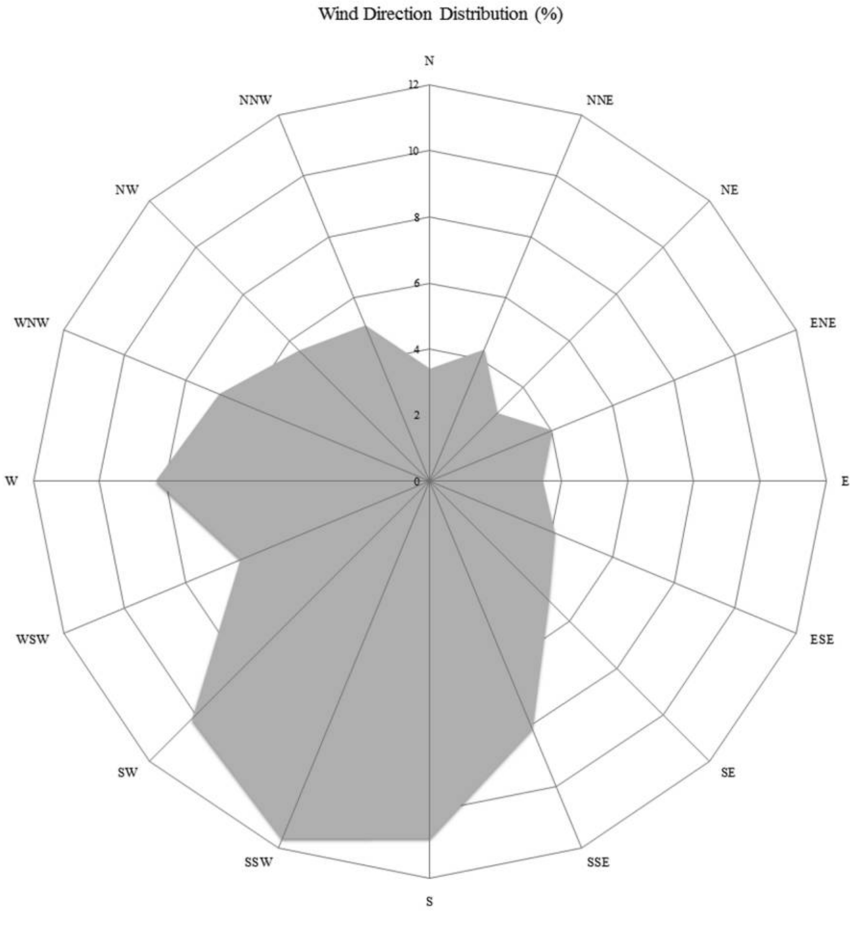

Figure 1. Prevailing wind direction distribution at DET (Coleman Young Municipal Airport in Detroit, Michigan).

To proxy for the risk of lead-based paint exposure, we use census tract housing data from the US Census Bureau measuring the percentage of housing stock built prior to 1950. Following Miranda et al. (2011), we also measure the percentage of households receiving public assistance income, median home prices, and percentage of adult population with a high school education or greater to estimate the socioeconomic conditions of a child's neighborhood (i.e., census tract). Studies show that children of low socioeconomic status are at greater risk of presenting with elevated BLLs (Campanella and Mielke 2008; Zahran et al. 2009). Finally, we also measure population density since this correlates strongly with road density, and road density is a reasonably good proxy for prior period use of leaded automobile gasoline and consequent accumulation

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of lead in neighborhood roads and soils (Quinn 2013; Zahran et al. 2013). Table 1 reports descriptive statistics for all variables.

2.4. Econometric Models

To analyze whether child BLL is dose-responsive in airport distance, we estimate a series of random intercept generalized least squares and logistic regression models with child BLLs measured continuously and dichotomously. The use of time-invariant covariates (like airport distance) necessitates the use of random as opposed to fixed effects regression. For reasons discussed in the previous section, our analytic emphasis is on threshold response variables instead of a continuous measure of blood lead. We therefore restrict our presentation of reduced form equations to logit models. All regressions include a tract-specific random intercept (ζ_j) to account for unobserved characteristics or conditions at the tract scale (like the accumulation of lead in neighborhood roads and soils). The term Y indicates a BLL surpassing a given threshold for

Table 1. Descriptive Statistics

Variable	Mean	SD	Min	Max
Blood lead (μg/dL)	2.98	3.00	1	164
≥5 μg/dL	.16	.37	0	1
≥10 μg/dL	.03	.17	0	1
Distance GNIS airport (km)	4.35	2.13	.11	10.00
Distance FAAOP airport (km)	6.02	2.29	.47	9.99
PEA traffic (monthly)	406.09	267.06	1	1,766
Downwind (%)	12.04	4.53	1.7	31.85
Age	2.25	1.43	0	5
Male	.51	.51	0	1
Winter	.19	.40	0	1
Spring	.23	.42	0	1
Summer	.29	.46	0	1
Fall	.28	.45	0	1
Housing built <1950 (%)	37.34	24.38	0	100
Population density	4,419.77	3,855.84	2.21	19,392.68
Public assistance (%)	6.65	5.94	0	30.79
≥ high school education (%)	77.12	13.43	0	100
Median home price ($10,000)	9.27	5.29	1.43	85.4
Pb facility ≤2 km	.88	1.59	0	13
Year	2005.50	2.49	2001	2009

Note. Descriptive statistics on age of child, blood lead outcomes, and season of blood draw are reported for all fully observed children (N = 1,023,672) in Michigan from 2001 to 2009. Distance to nearest FAAOP airport, PEA traffic, and downwind descriptive information pertain to the subset of airports inventoried in the FAAOP system.

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concern; $Y = 1$ if blood lead is ≥ 5 μg/dL (or ≥ 10 μg/dL), and $Y = 0$ if blood lead is <5 μg/dL (or <10 μg/dL); Y is modeled, for child i in census tract j and month t, by the following reduced form logistic equation:

$$\begin{aligned}\text{Prob}\left(Y_{ijt} = 1 | D_j, M_i, A_i, Z_t, S_t, F_j, H_j, P_j, I_j\right) \\ = \Lambda\left[\alpha_{ij} + \beta_1 D_j + \Gamma_1 M_i + \Gamma_2 A_i + \Gamma_3 Z_t \right. \\ \left. + \Gamma_4 S_t + \lambda_1 F_j + \lambda_2 H_j + \lambda_3 P_j + \lambda_4 I_j + \zeta_j\right].\end{aligned} \tag{1}$$

Here, $\Lambda[\cdot]$ is the cumulative distribution function of the logistic distribution, α_{ij} is the model intercept, corresponding to the likelihood of a reference child in census tract j eclipsing a CDC-defined threshold, D_j is the distance (in km) of the population-weighted centroid of census tract j to the nearest GNIS airport, $M_i = 1$ if the child is male, A_i denotes a series of dummy variables corresponding to child age in years, Z_t is the year the blood sample was drawn, measured as a series of year dummy variables with 2001 as our reference year, S_t is the season a blood sample was drawn, F_j is an indicator variable that equals 1 if a lead facility operates within 2 km, H_j is the percentage of housing stock in a child's neighborhood built before 1950, P_j is the population density in the child's neighborhood, and I_j is a vector of neighborhood socioeconomic characteristics, including the percentage of households in a child's neighborhood receiving public assistance income, percentage of adults $\geq$ a high school education, and median home prices. In addition to measuring distance continuously, we examine categories of distance (<1 km, 1–2 km, 2–3 km, 3–4 km, with >4 km constituting our reference category) to check for nonlinearities in the relationship between child BLL and airport distance. This first test is meant to reproduce Miranda et al. (2011), with the addition of more covariates (accounting for other sources of lead exposure). Insofar as deposition of lead from piston-engine aircraft traffic is a source of blood lead in children, we expect the odds of a child eclipsing CDC reference values to decrease in distance from GNIS airports.

Our next test is designed to separate the flow of avgas from the stock of lead in the lived environment that circulates seasonally (see Laidlaw et al. 2012; Zahran et al. 2013). Following the tragic events of 9/11, aircraft traffic in the United States was substantially restricted. The effect of this aircraft traffic restriction is reflected in monthly aviation gasoline sales and deliveries, which were significantly lower than expected in September, October, and November of 2001.[9] Insofar as avgas sales proxy for the

9. We estimated the following fixed effects least squares model to observe the deposition shock effect: $\ln(G_{it}) = \beta_0 + \beta_1 shock + \Gamma_1 month + \Gamma_2 year + \varepsilon_i$, where G_i is the sale of aviation gasoline by prime suppliers in Michigan (in thousands of gallons) in month i, *shock* is an indicator variable $= 1$ if the observation is from September to November in 2001, *month* is a suite of monthly dummy variables (with January as our reference month), *year* is a suite of

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monthly level of lead deposition across GNIS airports, we analytically leverage the exogenous restriction of PEA traffic as a quasi-experiment in lead deposition. In the air traffic restriction period following 9/11, avgas consumption drops markedly, while atmospheric resuspension of lead-contaminated soils and road dust is unperturbed. We estimate the following model:

$$\begin{aligned}\mathrm{Prob}\left(Y_{ijt} = 1 \mid D_j, E_t, M_i, A_i, Z_t, S_t, F_j, H_j, P_j, I_j\right) \\ = \Lambda\left[\alpha_{ij} + \beta_1 D_j + \beta_2 E_t + \delta\left(D_j \times E_t\right) + \Gamma_1 M_i + \Gamma_2 A_i \right. \\ \left. + \Gamma_3 Z_t + \Gamma_4 S_t + \lambda_1 F_j + \lambda_2 H_j + \lambda_3 P_j + \lambda_4 I_j + \zeta_j\right].\end{aligned} \tag{2}$$

The definition of terms carries over from equation (1). The term E_t equals 1 if a child's blood was drawn during the episode of depressed avgas sales from 9/2001 to 11/2001. The impact of the deposition shock is captured by the coefficient β_2. The coefficient of interaction (δ) measures the combined effect of airport proximity (D_j) and the episode indicator (E_t). To the extent that child BLL is linked to avgas deposition, β_2 should be negative and δ positive, the latter expectation reflecting the dissipation of the shock effect in distance.

While the above test works to identify a distance effect, it imprecisely assumes that PEA traffic is the same across airports and that prevailing winds behave uniformly at each airport. For a subset of all 27 airports inventoried in the FAAOP system, we obtained data on the monthly flow of PEA traffic as well as prevailing wind direction distribution data. We use these data to analyze whether child BLLs increase with the volume of PEA traffic and downwind risk. Importantly, the next tests exploit variation in PEA traffic determined by exogenous fluctuations in local weather conditions.[10] They also leverage prevailing wind direction as an exogenous source of varia-

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dummy variables for the year of observation (with 2001 as our reference year) and ε_i is our error term. Results on our shock variable indicate that avgas sales declined significantly in the aftermath of 9/11 ($b_1 = -0.57$, $p = .015$). This result is corroborated by a fixed effects least square model of PEA traffic in our subset of FAAOP airports. Clustering error at the airport level, we estimated the following: $\ln(P_{ij}) = \beta_0 + \beta_1 shock + \Gamma_1 month + \Gamma_2 year + \Gamma_3 airport_j + \varepsilon_{ij}$, where P_{ij} is the volume of PEA operations (departures and arrivals) in month i at FAAOP airport j, *shock*, *month*, and *year* are the same as before, and *airport* is a suite of dummy variables corresponding to each FAAOP airport (with APN, Alpena, as our reference airport). In the months following 9/11, PEA traffic declined significantly ($b_1 = -0.14$, $p = .011$).

10. Local conditions vary meaningfully across airport facilities examined. The average annual number of snow days and precipitation inches varies considerably across airports. For instance, CIU (in the northeast end of Michigan's Upper Peninsula) has more than twice the number of average annual snow days as DET (that is 9 km northeast of Detroit's central business district). Not only does total precipitation vary across examined airports, but so does the peak month of precipitation and the percentage difference between peak and trough months over the calendar year. Variation in precipitation across airports, and within airports in time, importantly determine the level of PEA traffic and consequent deposition of lead on neighborhoods nearby.

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tion with respect to the problem of residential selection. The augmented regression model is:

$$\begin{aligned}\text{Prob}\left(Y_{ijt} = 1 | D_j, T_{jt}, W_j, M_i, A_i, Z_t, S_t, F_j, H_j, P_j, I_j\right) \\ = \Lambda\left[\alpha_{ij} + \beta_1 D_j + \beta_2 T_{jt} + \beta_3 W_j + \Gamma_1 M_i + \Gamma_2 A_i \right. \\ \left. + \Gamma_3 Z_t + \Gamma_4 S_t + \lambda_1 F_j + \lambda_2 H_j + \lambda_3 P_j + \lambda_4 I_j + \zeta_j\right].\end{aligned} \quad (3)$$

All terms carry over from equation (1), with the addition of T_{jt} representing the monthly sum of PEA arrivals and departures at the nearest airport corresponding to the month of child blood draw, and W_j denoting the percentage of prevailing wind days that drift in the direction of child's residential location.

Finally, we analyze various two-way and three-way interactions of the main treatment variables. For instance, we estimate how the PEA traffic effect (T) varies by distance (D) and downwind risk (W). The expectation is that, to the extent that PEA traffic is an important source of elevated BLL risk, the PEA traffic effect should attenuate in distance and amplify in downwind days. We estimate the following:

$$\begin{aligned}\text{Prob}\left(Y_{ijt} = 1 | D_j, T_{jt}, W_j, M_i, A_i, Z_t, S_t, F_j, H_j, P_j, I_j\right) \\ = \Lambda\left[\alpha_{ij} + \beta_1 D_j + \beta_2 T_{jt} + \beta_3 W_j + \delta\left(D_j \times T_{jt}\right) \right. \\ + \varphi\left(W_j \times T_{jt}\right) + \vartheta\left(D_j \times W_j \times T_{jt}\right) + \Gamma_1 M_i + \Gamma_2 A_i \\ \left. + \Gamma_3 Z_t + \Gamma_4 S_t + \lambda_1 F_j + \lambda_2 H_j + \lambda_3 P_j + \lambda_4 I_j + \zeta_j\right].\end{aligned} \quad (4)$$

The interaction between PEA traffic and tract distance is captured by δ.[11] The effect of PEA traffic on downwind risk is captured by φ. Moreover, the three-way effect of distance, traffic, and downwind risk is captured by ϑ. Here, we expect the risk of elevated blood lead from PEA traffic (T) to amplify in downwind days (W) and to dissipate in distance (D).

3. RESULTS

Table 2 reports descriptive statistics on mean BLLs and the proportion of observed children exceeding present and past CDC reference values. All covariates behave as expected. The proportion of children with BLL above relevant thresholds increases

11. This test also addresses a modest sampling gradient in distance to airports. Children residing near airports are slightly more likely to have their blood sampled for lead content. The sampling ratio increases less than 1% ($b = -0.86$, 95% CI: −1.13, −0.58) for every kilometer in distance from the nearest airport, equal to about 9 fewer children sampled per kilometer of distance.

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in proximity to the nearest GNIS airport, in the monthly flow of PEA traffic, in the percentage of wind days that drift in the direction of child's residential neighborhood, in the percentage of housing built before 1950, in summer and fall relative to spring and winter, in proximity to lead-emitting TRI facilities, and in neighborhood population density.

Table 3 reports coefficients predicting child BLLs (measured continuously) and odds of a child's BLL exceeding present (≥ 5 μg/dL) and past (≥ 10 μg/dL) CDC reference values. Columns 1 and 4 report results from random intercept least squares models with child BLL measured continuously. In column 4, and as compared to children at >4 km from a GNIS airport, we find that the BLLs of children residing <1 km, 1–2 km, and 2–3 km of a GNIS airport are 5.7%, 2.9%, and 2.4% higher, respectively. By exponentiation of the coefficient in column 2 ($e^{-0.025}$), we find that the risk of a child eclipsing the CDC reference value of 5 μg/dL decreases by 2.5% (95% CI: −3.4, −1.5) for every kilometer from a GNIS airport. Similarly, in column 3, we find that a 1 km increase in neighborhood distance from a GNIS airport reduces the odds of a child's BLL exceeding 10 μg/dL by a multiplicative factor of 0.971 ($e^{-0.03}$). Columns 5 and 6 divide airport distance (D) into discrete categories ($D \leq 1$ km; 1 km $> D <$ 2 km; 2 km $> D <$ 3 km; and 3 km $> D <$ 4 km; and $D >$ 4 km).

In column 5, as compared to children residing >4 km from a GNIS airport, children at <1 km, 1–2 km, and 2–3 km are 25.2% ($e^{0.225}$), 16.5% ($e^{0.153}$), and 9.1% ($e^{0.087}$) more likely to present with a BLL reading ≥ 5 μg/dL, respectively. Similarly, the odds of eclipsing the CDCs past threshold of concern (≥ 10 μg/dL) increases in airport proximity. As shown in column 6, and as compared to children residing >4 km from a GNIS airport, children at <1 km and 1–2 km are 44.9% ($e^{0.371}$) and 24.9% ($e^{0.222}$) more likely to supersede a BLL of ≥ 10 μg/dL, respectively. Thus, consistent with Miranda et al. (2011), child BLLs decrease dose-responsively in distance, with the risk of elevated blood lead leveling at approximately 2–3 km from the nearest GNIS airport.

Before proceeding, it is worth noting the intuitive behavior of other variables known to influence BLL outcomes. For instance, in column 2, a unit increase in the percentage of housing stock built prior to 1950—a common proxy for the risk of Pb-based paint exposure—increases the child's odds of eclipsing the CDCs current threshold of 5 μg/dL by a factor of 1.019 (95% *CI*: 1.018, 1.021). The econometric model also detects the known seasonality in child BLL (Zahran et al. 2013), showing that, as compared to the reference seasons of winter/spring, children having their blood drawn in summer ($e^{0.313} = 1.37$) and fall ($e^{0.220} = 1.25$) months have significantly higher odds of having BLL ≥ 5 μg/dL.

Table 4 reports results from our quasi-experiment leveraging the fall off in air traffic after 9/11, 2001. We analyze the likelihood of a child's BLL eclipsing various thresholds (including 3, 5, and 10 μg/dL) as well the response of child BLL measured continuously. The coefficients of interest are our treatment period term capturing the BLL of children sampled in the avgas deposition shock period following 9/11, and our

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Table 2. Proportion of Children Eclipsing 5 and 10μg/dL and Mean Blood Lead by Covariates

	Proportion $\geq$5 μg/dL	Proportion $\geq$10 μg/dL	Mean μg/dL	Two-Sample *t*-Statistic
Distance to GNIS airport (km):				
>P.50	.144	.024	2.82	–69.60
<P.50	.191	.038	3.23	
Distance to FAAOP airport (km):				
>P.50	.177	.036	3.14	–55.37
<P.50	.252	.055	3.76	
Piston engine aircraft:				
>P.50	.227	.053	3.58	21.74
<P.50	.203	.039	3.33	
Downwind (%):				
>P.50	.231	.050	3.57	21.17
<P.50	.199	.042	3.33	
Sex:				
Male	.167	.031	3.02	17.81
Female	.156	.028	2.92	
Age of child:				
<1 year	.097	.012	2.38	–75.43
1 year	.140	.024	2.79	–48.71
2 years	.199	.040	3.33	52.67
3 years	.187	.035	3.19	33.31
4 years	.163	.029	2.97	–1.38
5 years	.171	.034	3.02	4.00
% housing built <1950:				
>P.50	.255	.053	3.77	2.9e+02
<P.50	.069	.007	2.19	
Season:				
Winter	.147	.026	2.85	–23.91
Spring	.146	.024	2.82	–31.56
Summer	.176	.035	3.11	29.21
Fall	.171	.032	3.05	16.67
Population density:				
>P.50	.233	.048	3.59	2.2e+02
<P.50	.091	.012	2.37	
% public assistance:				
>P.50	.253	.052	3.76	2.8e+02
<P.50	.072	.008	2.20	
% high school+:				
>P.50	.090	.011	2.36	–221.70
<P.50	.235	.048	3.60	

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Table 2 (*Continued*)

	Proportion ≥5 μg/dL	Proportion ≥10 μg/dL	Mean μg/dL	Two-Sample *t*-Statistic
Median home price:				
>P.50	.072	.008	2.20	−282.62
<P.50	.252	.051	3.75	
Pb facility <2 km:				
Yes	.226	.046	3.52	1.5e+02
No	.120	.019	2.62	
Year:				
>2005	.114	.017	2.64	−146.82
<2005	.216	.044	3.58	

Note. Blood lead outcomes by sex, age of child, % housing built <1950, season of blood draw, population density, % public assistance, % high school+, median home price, Pb facility count, and year are from all observed children (N = 1,023,672) in Michigan from 2001 to 2009, whereas blood lead outcomes by distance to FAAOP airport, PEA traffic, and downwind (%) are from children (N = 364,292) for our subset of 27 FAAOP airports.

difference-in-differences term, which captures the interaction between airport proximity and treatment period. Analyses are limited to the years 2001 to 2003, and the months of June to December.[12] Column 1 shows that children sampled in the deposition shock period had BLLs 4.9% lower (95% CI: −0.064, −0.034) than children sampled outside the deposition shock period. As expected, the effect fades significantly with distance to airport.

Similarly, column 2 shows that the odds of eclipsing 3 μg/dL declined by 13.5% ($1 - e^{-0.145}$) among children sampled in the treatment period, with the effect declining ~2.6% for every 1 km in distance to airport. Column 3 shows the risk of child BLL exceeding the CDCs current reference value. Other things held equal, children sampled in the deposition shock period had significantly lower odds of presenting a BLL reading ≥5 μg/dL. On average, treated children experienced an 11% ($1 - e^{-0.117}$) decrease (95% CI: −16.5%, −5.3%) in the probability of elevated BLL (≥5 μg/dL). While this beneficial effect appears to fade with distance from the nearest GNIS airport (b = 0.005), the interaction coefficient is not statistically significant.

While the results in tables 3 and 4 corroborate and extend Miranda et al. (2011), they do not account for the role of PEA traffic volume in determining the relationship

12. We thank two anonymous reviewers for suggesting we narrow the time window to limit temporal and seasonal confounding.

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Table 3. Random Intercept Logistic and Generalized Least Squares Coefficients Predicting Elevated BL (≥5 and 10 μg/dL) and BLLs in Children in Michigan Residing <10 km from an Airport

	ln (μg/dL) (1)	≥5 μg/dL (2)	≥10 μg/dL (3)	ln (μg/dL) (4)	≥5 μg/dL (5)	≥10 μg/dL (6)
Distance to airport	–.007***	–.025***	–.030***			
	(.001)	(.005)	(.009)			
Reference = distance ≥4 km:						
<1 km				.057***	.225***	.371***
				(.018)	(.067)	(.120)
1–2 km				.029***	.153***	.222***
				(.009)	(.037)	(.080)
2–3 km				.024***	.087***	.022
				(.009)	(.033)	(.061)
3–4 km				.012	.053	–.026
				(.008)	(.033)	(.058)
Reference = age <1:						
Age 1	.174***	.709***	1.044***	.174***	.709***	1.044***
	(.003)	(.021)	(.047)	(.003)	(.021)	(.047)
Age 2	.265***	.993***	1.367***	.265***	.993***	1.367***
	(.003)	(.022)	(.048)	(.003)	(.022)	(.048)
Age 3	.192***	.743***	1.051***	.192***	.743***	1.051***
	(.003)	(.022)	(.046)	(.003)	(.022)	(.046)
Age 4	.130***	.539***	.820***	.130***	.539***	.820***
	(.003)	(.022)	(.048)	(.003)	(.022)	(.048)
Age 5	.093***	.481***	.865***	.0934***	.481***	.865***
	(.003)	(.025)	(.042)	(.003)	(.024)	(.042)

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Male	.030***	.116***	.132***	.030***	.116***	.132***
	(.001)	(.006)	(.012)	(.001)	(.006)	(.012)
Reference = winter/spring:						
Summer season	.078***	.313***	.439***	.078***	.313***	.439***
	(.002)	(.009)	(.016)	(.002)	(.009)	(.016)
Fall season	.059***	.220***	.293***	.059***	.220***	.293***
	(.002)	(.009)	(.016)	(.002)	(.009)	(.016)
% housing built <1950	.005***	.019***	.026***	.005***	.019***	.025***
	(.000)	(.001)	(.001)	(.000)	(.001)	(.001)
Population density	.024***	.025	.127***	.024***	.031*	.137***
	(.004)	(.017)	(.025)	(.004)	(.017)	(.025)
% public assistance	.0241***	.071***	.082***	.024***	.071***	.083***
	(.001)	(.004)	(.005)	(.001)	(.004)	(.005)
% ≥ high school education	–.002***	–.007***	–.008***	–.002***	–.007***	–.008***
	(.000)	(.002)	(.002)	(.000)	(.002)	(.002)
Median home price ($10,000)	–.005***	–.021***	–.010**	–.004***	–.021***	–.010*
	(.001)	(.003)	(.006)	(.001)	(.003)	(.006)
Pb facility <2 km	.005	.007	.013	.005**	.007	.014
	(.003)	(.011)	(.015)	(.003)	(.011)	(.015)
Reference = year 2001:						
Year 2002	–.093***	–.266***	–.310***	–.093***	–.266***	–.310***
	(.003)	(.014)	(.027)	(.003)	(.012)	(.027)
Year 2003	–.215***	–.591***	–.641***	–.215***	–.591***	–.641***
	(.003)	(.015)	(.028)	(.003)	(.015)	(.028)
Year 2004	–.254***	–.600***	–.741***	–.254***	–.600***	–.741***
	(.003)	(.016)	(.030)	(.003)	(.016)	(.030)

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Table 3 (*Continued*)

	ln (μg/dL) (1)	$\geq$5 μg/dL (2)	$\geq$10 μg/dL (3)	ln (μg/dL) (4)	$\geq$5 μg/dL (5)	$\geq$10 μg/dL (6)
Year 2005	−.243***	−.628***	−.674***	−.243***	−.628***	−.674***
	(.003)	(.019)	(.031)	(.003)	(.019)	(.031)
Year 2006	−.300***	−.854***	−1.021******	−.300***	−.854***	−1.021***
	(.003)	(.019)	(.033)	(.003)	(.019)	(.033)
Year 2007	−.323***	−.906***	−1.069***	−.323***	−.906***	−1.069***
	(.003)	(.021)	(.035)	(.003)	(.021)	(.035)
Year 2008	−.392***	−1.212***	−1.302***	−.392***	−1.212***	−1.302***
	(.003)	(.019)	(.036)	(.003)	(.019)	(.036)
Year 2009	−.388***	−1.350***	−1.498***	−.388***	−1.350***	−1.498***
	(.003)	(.021)	(.038)	(.003)	(.021)	(.038)
Constant	.747***	−2.591***	−5.541***	.710***	−2.734***	−5.672***
	(.040)	(.120)	(.186)	(.031)	(.126)	(.186)
Log pseudolikelihood		−378,483.29	−114,715.91		−378,480.7	−114,708.21
Wald χ^2	10,219.15	12,501.98	7,020.23	54,572.13	12,504.77	7,023.79
N	1,023,672	1,023,672	1,023,672	1,023,672	1,023,672	1,023,672
Number of tracts	2,431	2,431	2,431	2,431	2,431	2,431

Note. Robust standard errors clustered by census tract in parentheses. All children surveilled in Michigan Department of Community Health data system from 2001 to 2009 that reside within 10 km of a GNIS airport are included in the analysis. Distance is measured in kilometers from the population-weighted centroid of each census tract where a child resides to the nearest GNIS airport. The blood lead thresholds of ≥5 μg/dL and ≥10 μg/dL correspond to the CDCs current and past reference values for elevated blood lead, respectively.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

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Table 4. Difference-in-Differences Random Intercept Logistic and Generalized Least Squares Coefficients Predicting Elevated BL (≥3, 5, and 10 μg/dL) and BLLs in Children in Michigan Residing <10 km from an Airport

	ln (μg/dL) (1)	≥3 μg/dL (2)	≥5 μg/dL (3)	≥10 μg/dL (4)
Distance to airport	−.008***	−.026***	−.025***	−.020
	(.002)	(.008)	(.008)	(.014)
Treatment period	−.049***	−.145***	−.117***	−.048
	(.008)	(.031)	(.032)	(.053)
Distance to airport × Treatment period	.005**	.025**	.005	−.013
	(.002)	(.011)	(.010)	(.017)
Reference = age < 1:				
Age 1	.259***	.708***	.835***	1.180***
	(.007)	(.031)	(.038)	(.070)
Age 2	.372***	1.032***	1.106***	1.432***
	(.008)	(.032)	(.038)	(.074)
Age 3	.259***	.747***	.771***	.965***
	(.008)	(.032)	(.039)	(.072)
Age 4	.187***	.530***	.578***	.801***
	(.007)	(.033)	(.039)	(.070)
Age 5	.152***	.386***	.566***	.873***
	(.009)	(.037)	(.042)	(.075)
Male	.034***	.100***	.107***	.127***
	(.003)	(.012)	(.014)	(.023)
Reference = winter/spring:				
Summer season	.111***	.275***	.411***	.549***
	(.006)	(.026)	(.032)	(.051)
Fall season	.090***	.243***	.314***	.380***
	(.007)	(.026)	(.032)	(.051)
% housing built <1950	.006***	.017***	.020***	.027***
	(.000)	(.001)	(.001)	(.002)
Population density	.033***	.066***	.122***	.154***
	(.006)	(.024)	(.023)	(.034)
% public assistance	.027***	.068***	.076***	.088***
	(.002)	(.005)	(.005)	(.006)
% ≥ high school education	−.002***	−.003	−.007***	−.011***
	(.001)	(.002)	(.002)	(.003)
Median home price ($10,000)	−.005***	−.030***	−.023***	−.002
	(.001)	(.004)	(.006)	(.010)
Pb facility <2 km	.011***	.040**	.019	.019
	(.004)	(.017)	(.015)	(.021)

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Table 4 (*Continued*)

	ln (μg/dL) (1)	≥3 μg/dL (2)	≥5 μg/dL (3)	≥10 μg/dL (4)
Reference = year 2001:				
Year 2002	−.126***	−.386***	−.364***	−.315***
	(.006)	(.025)	(.024)	(.042)
Year 2003	−.233***	−.687***	−.684***	−.650***
	(.006)	(.028)	(.025)	(.043)
Constant	.528***	−1.120***	−2.951***	−5.767***
	(.046)	(.173)	(.178)	(.256)
Log pseudolikelihood		−78,307.92	−66,301.19	−27,316.44
Wald χ^2	10687.35	4,293.10	5,325.21	2,603.60
N	139,802	139,802	139,802	139,802
Number of tracts	2,420	2,420	2,420	2,420

Note. Robust standard errors clustered by census tract in parentheses. All children who reside within 10 km of a GNIS airport ($N = 448$) and sampled from 2001 to 2003, and in the months of June to December are included in the analysis. The treatment period is September to November in 2001 corresponding to measurable downward shocks in avgas sales and piston-engine aircraft traffic in Michigan following 9/11 (see n. 11).

* $p < .10$.

** $p < .05$.

*** $p < .01$.

between airport distance and lead exposure risk. A more telling test would evaluate BLL levels in response to PEA traffic. We begin with an ecological view of the data.

Figure 2 (panel A) shows the joint movement of monthly average BLL over all measured children in Michigan (residing <10 km from 27 airports with valid PEA traffic), as well as the average monthly sum of PEA departures and arrivals (at the same 27 airports). Both series are standardized ($\mu = 0$, $\sigma = 1$). The series share strikingly similar seasonality and drift downward together in time. The temporal correlation is strong ($r = 0.823$). While figure 2, panel A, is strongly suggestive of an avgas and BLL link, recall that soil resuspension is a known source of seasonal variation in child BLLs (Zahran et al. 2013). Panel B addresses this potential confounding. Again, time is on the x-axis, but now monthly average BLL is divided into two categories: above average and below average PEA traffic. The series diverge intuitively with the high traffic series lying strictly above the low traffic series.

Narrowing in, table 5 reports coefficients that predict the likelihood of threshold exceedance as a function of PEA traffic and wind direction. The population is restricted to children residing within 10 km of an FAAOP airport (with valid monthly PEA traffic). Recall, to estimate the effect of PEA traffic, children are matched spatially to the

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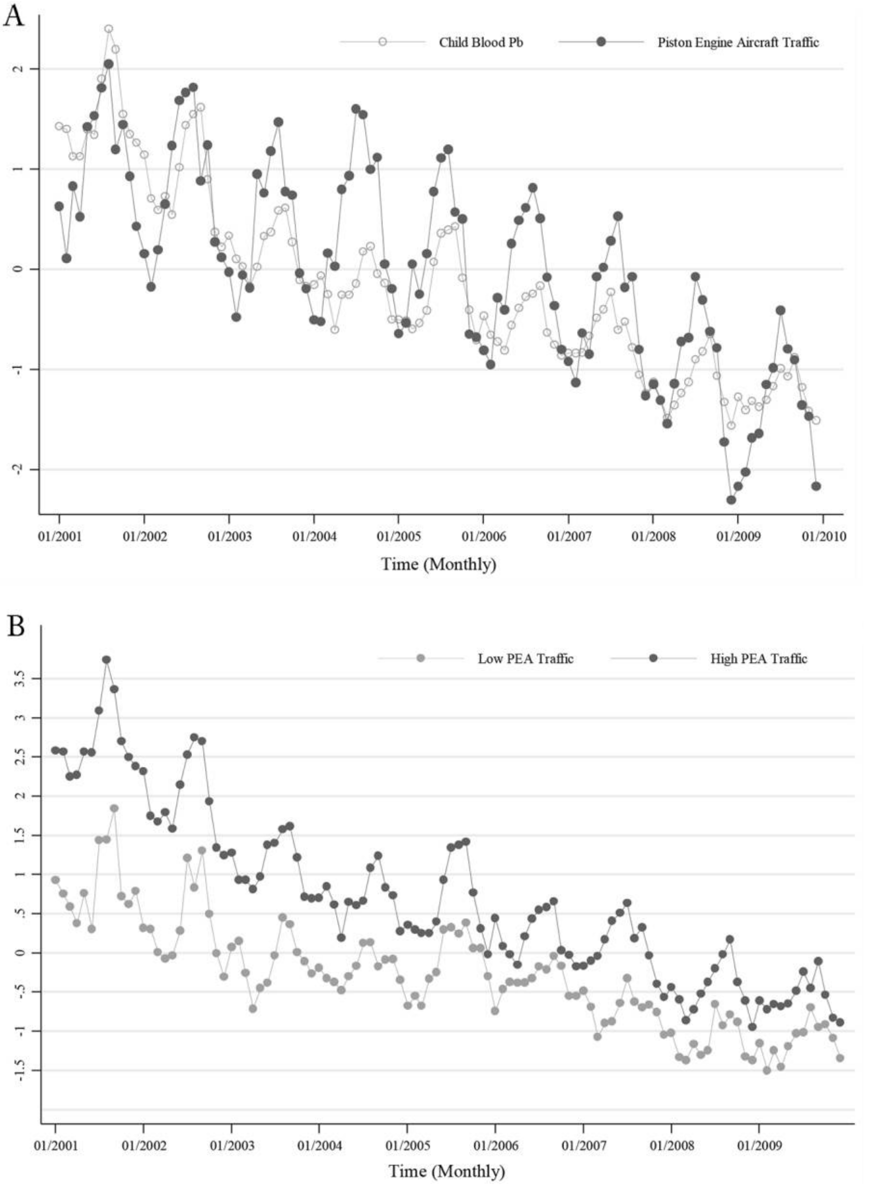

Figure 2. Monthly blood Pb (of children ≤10 km of traffic airport) and piston engine aircraft traffic in time and blood lead levels by PEA traffic. Average monthly blood lead data correspond to all children in Michigan residing within 10 km of a FAAOP airport with valid PEA traffic data. Both the monthly blood lead and PEA traffic series are *z*-score standardized with mean = 0, and standard deviation = 1.

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Table 5. Random Intercept Logistic Coefficients Predicting Elevated BL (≥5 and 10 μg/dL) and BLLs in Children in Michigan Residing <10 km from an Airport with Valid Piston Engine Aircraft Traffic

	≥5 μg/dL (1)	≥10 μg/dL (2)	≥5 μg/dL (3)	≥10 μg/dL (4)	≥5 μg/dL (5)	≥10 μg/dL (6)
Distance to airport	−.035***	−.035**	−.030***	−.030**	−.030***	−.030**
	(.009)	(.014)	(.010)	(.014)	(.010)	(.014)
PEA traffic	.028***	.035***	.034***	.038***	.033***	.038***
	(.006)	(.010)	(.006)	(.010)	(.006)	(.010)
Downwind	.018***	.019***	.016***	.019***	.014***	.017***
	(.005)	(.007)	(.005)	(.007)	(.005)	(.007)
Distance × PEA traffic			−.011***	−.010***	−.011***	−.010***
			(.002)	(.003)	(.002)	(.003)
Downwind × PEA traffic			.003**	−.000	.002**	−.000
			(.001)	(.002)	(.001)	(.002)
Distance × Downwind					.005**	.004
					(.002)	(.003)
Distance × PEA traffic × Downwind					.001**	.000
					(.000)	(.001)
Reference = age <1:						
Age 1	.894***	1.230***	.895***	1.231***	.895***	1.231***
	(.029)	(.061)	(.029)	(.061)	(.029)	(.061)

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Age 2	1.223***	1.598***	1.225***	1.599***	1.225***	1.599***
	(.028)	(.060)	(.028)	(.060)	(.029)	(.06)
Age 3	.983***	1.275***	.985***	1.276***	.985***	1.276***
	(.028)	(.058)	(.028)	(.058)	(.028)	(.058)
Age 4	.763***	1.023***	.763***	1.024***	.764***	1.024***
	(.028)	(.059)	(.028)	(.059)	(.028)	(.059)
Age 5	.692***	1.039***	.694***	1.040***	.694***	1.040***
	(.031)	(.061)	(.031)	(.061)	(.031)	(.061)
Male	.117***	.131***	.117***	.132***	.117***	.131***
	(.010)	(.017)	(.010)	(.017)	(.010)	(.017)
Reference = winter/spring:						
Summer season	.295***	.403***	.284***	.394***	.282***	.393***
	(.014)	(.023)	(.012)	(.023)	(.014)	(.023)
Fall season	.204***	.278***	.198***	.274***	.198***	.274***
	(.012)	(.021)	(.013)	(.021)	(.013)	(.021)
% housing built <1950	.020***	.028***	.020***	.027***	.020***	.027***
	(.001)	(.002)	(.001)	(.002)	(.001)	(.002)
Population density	.130***	.137***	.132***	.134***	.128**	.135***
	(.029)	(.041)	(.028)	(.041)	(.028)	(.041)
% public assistance	.073***	.085***	.073***	.085***	.072***	.084***
	(.006)	(.007)	(.006)	(.008)	(.006)	(.007)
Median home price ($10,000)	–.017***	–.001	–.017***	–.002	–.017***	–.002
	(.005)	(.008)	(.005)	(.008)	(.005)	(.008)

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Table 5 (*Continued*)

	≥5 μg/dL (1)	≥10 μg/dL (2)	≥5 μg/dL (3)	≥10 μg/dL (4)	≥5 μg/dL (5)	≥10 μg/dL (6)
% ≥ high school education	−.009***	−.014***	−.009***	−.015***	−.010***	−.015***
	(.002)	(.003)	(.002)	(.003)	(.002)	(.003)
Pb facility <2 km	.012	.011	.014	.019	.021	.018
	(.016)	(.024)	(.017)	(.024)	(.017)	(.025)
Reference = year 2001:						
Year 2002	−.207***	−.170***	−.205***	−.167***	−.203***	−.166***
	(.020)	(.032)	(.020)	(.032)	(.020)	(.032)
Year 2003	−.507***	−.530***	−.500***	−.525***	−.497***	−.523***
	(.022)	(.037)	(.023)	(.037)	(.023)	(.037)
Year 2004	−.542***	−.605***	−.535***	−.599***	−.532***	−.598***
	(.024)	(.037)	(.024)	(.037)	(.024)	(.038)
Year 2005	−.510***	−.490***	−.494***	−.477***	−.488***	−.475***
	(.025)	(.041)	(.026)	(.042)	(.026)	(.042)
Year 2006	−.720***	−.856***	−.700***	−.841***	−.694***	−.839***
	(.025)	(.046)	(.026)	(.047)	(.026)	(.047)

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Year 2007	−.771***	−.928***	−.748***	−.910***	−.742***	−.908***
	(.028)	(.052)	(.029)	(.052)	(.029)	(.053)
Year 2008	−1.120***	−1.179***	−1.099***	−1.162***	−1.093***	−1.160***
	(.029)	(.052)	(.029)	(.052)	(.029)	(.053)
Year 2009	−1.232***	−1.371***	−1.207***	−1.352***	−1.201***	−1.350***
	(.035)	(.059)	(.035)	(.059)	(.035)	(.059)
Constant	−2.984***	−5.738***	−2.849***	−5.554***	−2.800***	−5.522***
	(.231)	(.304)	(.212)	(.280)	(.211)	(.280)
Log pseudolikelihood	−152,450.56	−55,391.70	−152,416.68	−55,383.64	−152,405.51	−55,383.67
Wald χ^2	6,603.20	4,111.73	6,868.49	4,309.68	6,985.19	4,319.15
N	364,292	364,292	364,292	364,292	364,292	364,292
Number of tracts	745	745	745	745	745	745

Note. Robust standard errors clustered by census tract in parentheses. All children surveilled in Michigan Department of Community Health data system from 2001 to 2009 who reside within 10 km of a FAAOP airport ($N = 27$) are included in the analysis. Distance is measured in kilometers from the population-weighted centroid of each census tract where a child resides to the nearest FAAOP airport. PEA traffic corresponds to the observed number of departures and arrivals at a FAAOP airport matched to the month of blood draw for a potentially exposed child. The blood lead thresholds of ≥ 5 μg/dL and ≥ 10 μg/dL correspond to the CDCs current and past reference values for elevated blood lead, respectively. In columns 3–6, interacted variables are centered at their means.

* $p < .10$.
** $p < .05$.
*** $p < .01$.

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nearest FAAOP airport and temporally to the month of blood draw.[13] The reported test exploits variation in lead deposition from PEA traffic that is at least partly governed by exogenous local meteorological conditions. These conditions vary meaningfully across FAAOP airport locations.

Columns 1 and 2 report main effects for the distance, PEA traffic volume, and downwind risk variables. A 1 km increase in airport distance decreases the odds of a child eclipsing both present and past CDC thresholds by 3.4%. These distance effects for our subset of FAAOP airports are consistent with the distance effects reported in table 3 for all GNIS airports. Staying with columns 1 and 2, we find that an increase of 100 PEA operations per month increases the odds that a child's BLL $\geq$5 μg/dL by a factor of 1.028 (95% CI: 1.019, 1.040), and by a factor of 1.036 (95% CI: 1.017, 1.056) with respect to the odds of a child's BLL $\geq$10 μg/dL.

Columns 3 and 4 in table 5 report coefficients on the risk of elevated BLL among sampled children for two-way interactions involving PEA traffic. Intuitively, the PEA traffic exposure effect decreases in distance and increases in the percentage of downwind days. Thus, PEA traffic affects children proximate to airports more strongly than children distant from airports. The increased likelihood of exceeding 5 μg/dL for a given increase in PEA traffic of 100 operations decreases about 1% for every 1 km increase in airport distance. Regarding the interaction of PEA traffic and downwind risk, column 3 shows that the PEA traffic exposure effect increases a third of a percent for every 1% increase in downwind days. Columns 5 and 6 show coefficients for the three-way interaction of the main risk variables. As expected, prevailing wind direction functions to attenuate the airport proximity effect of PEA traffic. Given the positive coefficient on the two-way interaction of distance and downwind risk, the three-way interaction can be interpreted as showing that prevailing wind expands the radius of at-risk children.

Figure 3, panels A and B, plots results from column 3 in table 5. In both panels, the predicted probability of a child's BLL level $\geq$5 μg/dL is on the y-axis and PEA traffic is on the x-axis (moving in percentile rank units). Panel A summarizes the effect of PEA traffic at three distances (1 km, 4 km, and 7 km) from the nearest FAAOP airport. Predicted probabilities are derived with all other covariates fixed at their sample means. At 7 km from a FAAOP airport, change in PEA traffic has no meaningful effect on the

13. Results involving other operationalizations of PEA traffic exposure risk, including current month, previous month, 2 months previous, as well as 2- and 3-month rolling averages of PEA traffic are available from the authors on request. Including more than one operation of PEA traffic produces severe multicollinearity. The current month versus prior month PEA traffic correlation is very high ($r = 0.955$). Consistent with the known half-life of lead in the blood stream, we find that the PEA traffic effect dissipates in time lag. The 1-month lag coefficient is half the size of the current month PEA operationalization, with the effect of the 2-month lag on the likelihood of elevated blood lead being indistinguishable from chance.

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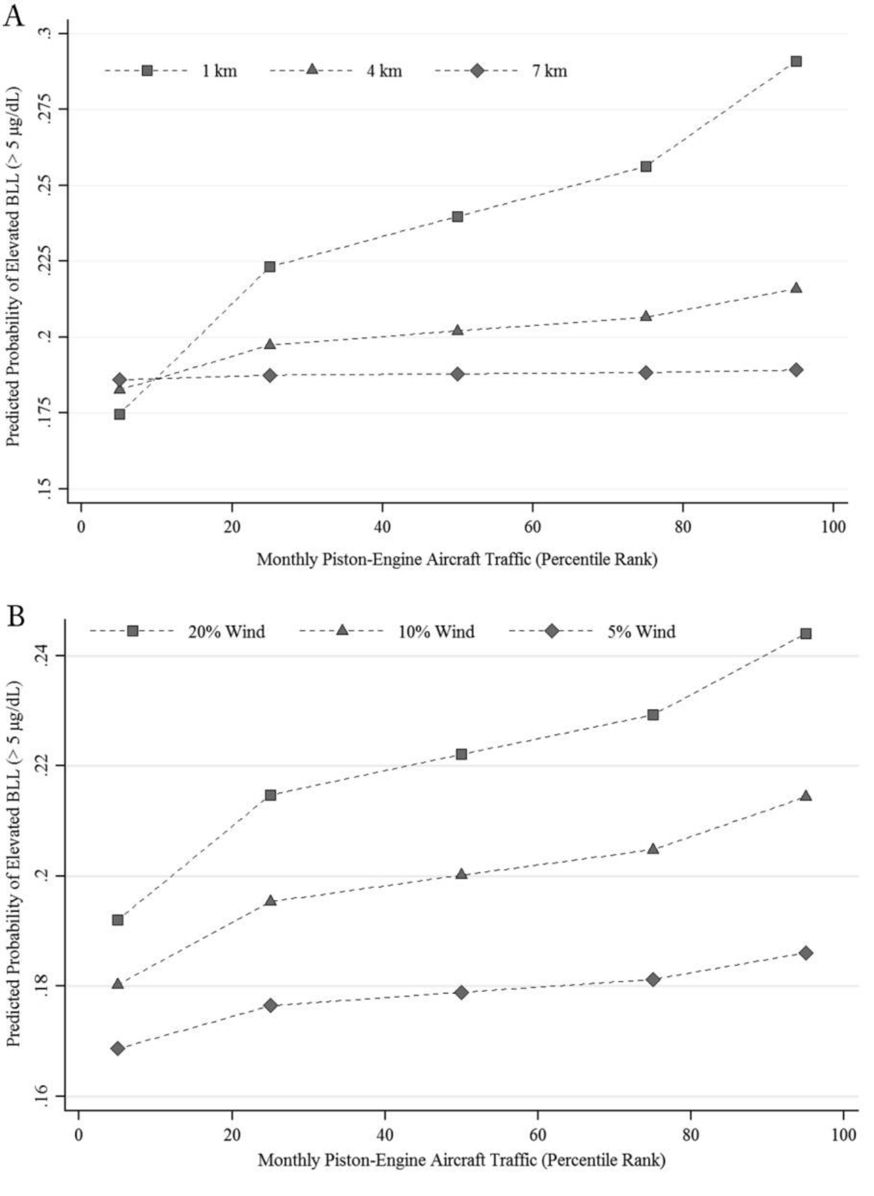

Figure 3. Predicted probabilities of elevated blood Pb (≥5 μg/dL) by PEA traffic and distance to nearest airport and by PEA traffic and downwind risk. Panels A and B graph results from column 3 in table 5. In both panels, the predicted probability of a child's BLL level ≥5 μg/dL is on the *y*-axis, and PEA traffic in on the *x*-axis (moving in percentile rank units). Panel A summarizes the effect of PEA traffic at three distances (1 km, 4 km, and 7 km) from the nearest FAAOP airport. Predicted probabilities are derived with all other covariates fixed at their sample means.

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BLLs of children. At 4 km from an airport, PEA traffic has a modest effect on the predicted probability of a child clearing the CDC's threshold of concern (≥5 μg/dL) when going from the 5th to the 95th percentile in PEA traffic. At 1 km, changing PEA traffic has a pronounced effect, increasing the predicted probability of threshold exceedance in going from the 5th to the 95th percentile in PEA traffic by about 70%. Thus, as expected, the PEA traffic effect amplifies in airport proximity.

Panel B summarizes the effect of PEA traffic at three downwind conditions—5%, 10%, and 20%—capturing the percentage of wind days that flow toward the neighborhood of a child. Other things held equal, the exceedance probability with respect to PEA traffic increases more steeply as we move from low to high downwind risk. At the 5th percentile in PEA traffic, children exposed to 5% downwind risk have a predicted probability of elevated BLL (≥5 μg/dL) of 0.169 (95% CI: 0.151, 1.186), while children facing 20% downwind risk have a predicted probability of elevated BLL of 0.192 (95% CI: 0.179, 0.205). At the 95th percentile in PEA traffic, the differential in the predicted probability of threshold exceedance among children at 5% versus 20% downwind risk increases (from 0.023 to 0.058).

4. SOCIAL BENEFITS

To quantify the significance of the results for policy, we conservatively estimate the social benefits of a reduction in monthly PEA traffic from the 50th (407) to the 10th (133) percentile in total departures and arrivals, equivalent to a two-thirds reduction in avgas deposition at the representative airport. Our choice to emphasize a movement from the 50th to 10th percentile corresponds to a reduction in PEA traffic at the representative airport to near zero, while staying within the support of the estimated distribution. This two-thirds reduction scenario also happens to coincide with the fraction of the existing fleet that could transition to motor vehicle gasoline with minimal adjustments (Kessler 2013). Marginal damage estimates behave consistently across various reduction scenarios.[14]

To estimate the social benefit of reduced avgas consumption, we leverage the regression coefficients from equation (3), and we use a standard syllogism in environmental health economics linking BLL to IQ point loss and IQ point loss to future earnings (Schwartz 1994; Grosse et al. 2002; Gould 2009). Table 6 summarizes the steps. First, according to Census Bureau data and tract distance calculations to the nearest airport, a total of 164,782 children reside within 2 km of an airport facility in Michigan. Columns A and B estimate the number of children falling into various

14. As discussed below, moving from the 50th to the 10th percentile implies a marginal damage estimate of $10.69 per gallon. In contrast, moving from the 95th to the 5th percentile implies $11.13 per gallon, 90th to 10th implies $10.95 per gallon, 75th to 25th implies $10.85 per gallon, and 25th to 10th implies $10.55 per gallon.

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Table 6. Estimated Gain in Present Discounted Value of Lifetime Earnings from IQ Point Gain from Reduction in PEA Traffic from 50th to 10th Percentile

	Risk Categories							
	Affected Children (No.) under 10th Percentile PEA Traffic (*A*)	Affected Children (No.) under 50th Percentile PEA Traffic (*B*)	Average BLL per Risk Bin (μg/dL) (C)	Average IQ Point Loss per μg/dL (*D*)	IQ Point Loss under 10th Percentile PEA Traffic (*E*)	IQ Point Loss under 50th Percentile PEA Traffic (*F*)	IQ Point Gain Attributable to PEA Traffic Decrease from 50th to 10th Percentile (G)	Gain in Present Discounted Value of Lifetime Earnings ($) from Decrease in PEA Traffic ($1 Million) (*H*)
< 5 μg/dL	132,806	131,151	2.40	0	0	0	0	$0
	[131,522–134,089]	[129,942–132,359]						
5–10 μg/dL	25,673	26,764	6.42	.513	84,552	88,145	3,593	$64.00
	[24,933–26,413]	[26,067–27,460]			[82,115–86,990]	[85,850–90,440]	[3,450–3,735]	[$61.46–$66.53]
10–20 μg/dL	5,398	5,870	13.55	.19	31,331	34,075	2,744	$48.88
	[4,980–5,815]	[5,460–6,281]			[28,906–33,756]	[31,693–36,456]	[2,700–2,787]	[$48.10–$49.65]
> 20 μg/dL	906	997	28.84	.11	7,250	7,982	732	$13.03
	[780–1,032]	[896–1,099]			[6,242–8,257]	[7,169–8,794]	[537–927]	[$9.57–$16.51]
Total	164,782	164,782			123,133	130,202	7,069	$125.90
					[117,263–129,003]	[124,712–135,690]	[6,687–7,449]	[$119.11–$132.69]

Note. Estimated count of children by BLL categories in columns A and B are derived from equation (3), setting T (representing the monthly sum of PEA arrivals and departures) at 133 for 10th percentile in PEA traffic and 407 for the 50th percentile in PEA traffic, and fixing other covariates at sample means. Row 2, column $E = A \times C \times D$; row 2, column $F = B \times C \times D$; row 2, column $G = F - E$; and column $H = G \times \$17$,

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BLL categories, ranging from <5 μg/dL to >20 μg/dL under 10th and 50th percentile levels of monthly PEA traffic respectively. These BLL categories correspond to observed breaks in the nonlinear association of IQ and BLL (Lanphear et al. 2005; Gould 2009). The count of children per BLL category is estimated by equation (3) under 10th and 50th percentile traffic scenarios.[15]

The number of children above the CDC's reference value of 5μg/dL is higher in column *B* (reflecting more PEA traffic) than in column *A* (reflecting less PEA traffic). Columns C and *D* indicate the average BLL level within each BLL category and the average IQ point loss per μg/dL, respectively. The marginal effects in column *D* are from Gould (2009), Lanphear et al. (2005), and Canfield et al. (2003). Columns *E* and *F* estimate IQ point loss under 10th and 50th percentile PEA traffic by multiplying the estimated number of affected children (in cols. *A* or *B*), the average BLL level per at-risk category, and the average IQ point loss per μg/dL by BLL category. The sum of IQ points gained in going from the 50th to the 10th percentile in PEA traffic (7,069 IQ points) is reported in column G. This reflects the difference between columns *F* and *E*.

Following others (Schwartz 1994; Salkever 1995; Grosse et al. 2002; Nevin et al. 2008), each IQ point gained corresponds to a gain in the present discounted value of lifetime earnings of $17,815 (2006 US$). Multiplying this by the sum of IQ points gained (7,069) gives a total social benefit of $126 million (95% CI: $119–$133 million). This benefit would be realized for subsequent cohorts of children (0–5 years of age) in Michigan. Assuming population density near airports and other conditions in Michigan generalize, this suggests a national benefit of about $4.9 billion.[16] It also implies an external social cost of $10.69 per gallon for currently formulated avgas in Michigan. This estimate is not comprehensive since it reflects gains to only a subset of the population (children ≤5 years of age), and it considers only one benefit channel (IQ loss). Including health care and special education costs averted, as well as behavioral and crime control costs, would lead to a higher estimate (Gould 2009).

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15. Fixing other covariates at their means, we estimate the proportion of children exceeding specified thresholds under 10th and 50th percentile PEA traffic scenarios. The derived proportions are then multiplied by the count of children in census tracts within 2 km of an airport (specifically, 164,782) to get the count of children per BLL category.

16. In Michigan, there are 164,782 children within 2 km of airports, while the corresponding national number is an estimated 6.4 million. Scaling the Michigan benefit estimate nationally, under the 50th percentile in PEA traffic, total IQ point loss attributable to PEA traffic is 405,583 and social damages are $7.2 billion. Nationally, under the 10th percentile in traffic, total IQ point loss attributable to PEA traffic is 129,740 and social damages are $2.3 billion. The difference in social damages under 50th and 10th percentile of PEA traffic gives our figure of $4.9 billion.

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5. CONCLUSION

The consequences of lead exposure in childhood are lasting. Neural-imaging studies find that adults exposed to lead as children have reduced gray matter in regions of the brain known to govern executive judgment, impulsivity and mood regulation (Cecil et al. 2008, 2011). Economists have convincingly linked these intellectual and socio-emotional traits of judgment and impulsivity to long-term life outcomes (Doyle et al. 2009; Cunha and Heckman 2010; Currie and Almond 2011). Consistent with this general literature on the long reach of childhood, Jessica Reyes (2015, 1) has shown that persons exposed to lead in early life experience "an unfolding series of adverse behavioral outcomes: behavior problems as a child, pregnancy and aggression as a teen, and criminal behavior as a young adult."

Past lead control efforts have generated sizable social benefits (Grosse et al. 2002; Gould 2009; Pichery et al. 2011; Jones 2012), with mean BLLs for children one to five years old declining from 14.9 μg/dL in 1976 to 1.7 μg/dL two decades later (Gould 2009). Despite this dramatic success, BLLs remain high for over half a million children in the United States (Zahran et al. 2011). The current study provides clear evidence that elevated BLLs in children proximate to airports is at least partly attributable to avgas deposition from piston-engine aircraft.

Specifically, the odds that a child's BLL will eclipse CDC thresholds for concern increases dose-responsively in proximity to airports, declines measurably in neighborhoods proximate to airports in the months following 9/11, increases dose-responsively in the flow of PEA traffic, and increases significantly in the percentage of downwind risk days. Meanwhile, statistical interactions between residential distance, PEA traffic, and downwind risk all behave in intuitive ways, supporting the claim that avgas deposition is an independent source of lead exposure risk for children. As shown in table 3, children residing within 1 km of a GNIS airport are 25% and 45% more likely to exceed present and past thresholds of concern than children at ≥4 km from an airport. As shown in figure 3, panel A, the predicted probability of exceeding the current CDC threshold for concern for a child residing within 1 km of airport nearly doubles in going from low (5th percentile) to high (95th percentile) PEA traffic.

According to the analysis, a hypothetical reduction in PEA traffic from the 50th to the 10th percentile would generate a 5-year cohort benefit of $126 million for Michigan and $4.9 billion nationwide.[17] Accompanying such a reduction, the number of children falling below the CDC current reference threshold of 5 μg/dL would increase

17. Our nationwide 5-year cohort benefit of $4.9 billion is similar to Wolfe et al.'s (2016) 1-year cohort estimate of $1.06 billion in economic damages from elevated atmospheric lead exposure using the Community Multi-Scale Air Quality model. Wolfe et al. (2016) note that the monetary impacts of aviation lead emissions are similar in magnitude to noise, climate change, and air quality degradation from all commercial operations.

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by about 1,600 children in Michigan and 64,000 children nationwide. To put this in perspective, the recent catastrophic failure of the water treatment system in Flint, Michigan, increased the number of children with elevated BLLs by approximately 200 (Hanna-Attisha et al. 2016).[18] The comparison is imperfect since the Flint water crisis occurred at a different time period, with a lower baseline fraction of children with BLLs $\geq 5\ \mu g/dL$, and because the Flint case involved explicit acts of commission. Nevertheless, the comparison demonstrates the large scale of social damages that can be attributed to the ongoing consumption of avgas in the United States.

Under current regulations, these damages are unpriced. An emission fee that forced consumers to internalize these costs—a tax of approximately $10 per gallon compared to a pump price of approximately $6[19]—would likely cause a rapid transition away from lead-formulated avgas by the roughly two-thirds of the existing PEA fleet for which the lead additive is noncritical (Kessler 2013). In addition, by creating strong incentives for innovation and for the gradual turnover of the lead-dependent fleet, such a policy would set the stage for the eventual phase out of lead from the aviation sector.

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18. Hanna-Attisha et al. (2016) find that the percentage of sampled children in Flint, Michigan, with elevated BLLs increased from 2.4% to 4.9% following the water source change. We derive the estimated count of affected children by the water source change by taking the count of children under five (8% of a population of 102,434, Census, April 1, 2010) multiplied by the figures reported by Hanna-Attisha et al.

19. Of course, the efficient emission tax would be applied to the lead content of gasoline, so the tax per gallon would vary for different formulations of avgas. The estimate of $10.69 applies to an average gallon of avgas sold in Michigan over the sample period. This is equivalent to $5.60 per gram of lead.

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