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Low-Level Lead Exposure and Children's Human Capital: Evidence from Piston-Engine Aircraft

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Abstract

How harmful are low levels of lead exposure to children's human capital development? We provide new causal evidence by exploiting a post-2007 surge in piston-engine aircraft activity, the largest remaining source of airborne lead emissions in the United States, driven by flight-training demand. Using a triple-differences design and longitudinal administrative data, we find that students attending schools within one mile of high-surge airports score 0.168 standard deviations lower on reading tests and are 6% and 25% less likely to graduate from high school and enroll in a public university, respectively. Estimated effects on behavioral outcomes are small and statistically insignificant.

JEL classification

I14, I24, Q53

Keywords

piston-engine aircraft, lead emissions, human capital development

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1 Introduction

Lead is a powerful neurotoxin with well-documented adverse effects on children's cognitive development, behavior, and long-run human capital (EPA, 2013; Reyes, 2015; Aizer and Currie, 2019). Despite the phaseout of major sources of lead emissions, including automobile gasoline, paint, and plumbing, lead exposure remains a pressing public health crisis.[1] Piston-engine aircraft are the largest remaining source of airborne lead emissions in the United States, with emissions concentrated around airports that are often located near residential neighborhoods and schools (AOPA, 2016; Santa Clara County, 2021).[2] EPA (2010) estimates indicate that 16 million people live, and 3 million children attend school, within one kilometer of an airport with piston-engine aircraft activity.

While the adverse effects of high levels of lead exposure on health, cognition, and behavior are well-established (Reyes, 2015; Aizer et al., 2018; Aizer and Currie, 2019; Grönqvist et al., 2020; Hollingsworth et al., 2022; Gazze et al., 2024), the impacts of low-level lead exposure are less clear and have received less attention in the literature. Additionally, we know little about whether, and to what extent, low-level lead exposure generates long-lasting adverse impacts.

One of the main challenges in studying the long-term impacts of lead exposure is the difficulty of obtaining comprehensive longitudinal data that link early childhood exposure to outcomes observed in adulthood. Another challenge lies in disentangling lead's effects from unobserved household and environmental factors that may confound estimates. Additionally, most studies rely on blood lead levels (BLLs) to measure exposure, which capture only recent exposure and may underestimate the cumulative impact of lead that accumulates in bones and other tissues over time.

In this paper, we ask whether low-level lead emissions from piston-engine aircraft affect children's human capital development. This question matters for two reasons. First, the relevant exposure levels are low relative to historical lead exposure from automobiles, paint, and plumbing. Whether such low-level exposure still generates detectable educational harm is a central question for environmental and

[1] Approximately one-third of all children globally have blood lead levels (BLLs) above 5 μg/dL, the action threshold set by the World Health Organization (WHO). In the US, nearly 600,000 children under the age of 5 had BLLs exceeding the reference value of 3.5 μg/dL (Rees and Fuller, 2020; Fabolude et al., 2024).

[2] Piston engine aircraft remain one of the few mobile sources still permitted to use leaded fuel. The most common aviation gasoline used by these aircraft, 100LL, contains up to 0.56 grams of lead per liter, or 2.12 grams per gallon (Federal Aviation Administration, 2019a). According to the U.S. Environmental Protection Agency (2008), PEA can account for up to two-thirds of the remaining lead emissions in the US.

human-capital policy. Second, aviation lead is an active regulatory issue. The Environmental Protection Agency has issued an endangerment finding for lead emissions from aircraft engines that operate on leaded fuel, and the Federal Aviation Administration's EAGLE initiative aims to eliminate leaded aviation fuel in piston-engine aircraft by 2030 (U.S. Environmental Protection Agency, 2023; Federal Aviation Administration, 2025). Evidence on the educational and economic consequences of this remaining source of lead exposure is therefore directly relevant to ongoing policy decisions.

We address the gaps and challenges faced by prior studies by leveraging a restricted-use longitudinal administrative dataset from the Texas Education Research Center (ERC). The ERC data link children's educational records from Kindergarten through postsecondary education with labor market outcomes, enabling us to estimate the effects of early childhood lead exposure on children's short- and long-run outcomes.

To address the potential selection issue in lead exposure, we exploit a natural experiment: the sharp increase in piston-engine aircraft (PEA) traffic after 2007 due to growing demand for pilots and increased flight training. Since initial certification and advanced ratings are conducted primarily in small PEAs, the flight training boom generated repeated takeoffs, landings, and localized operations by these lead-emitting aircraft. These changes created a substantial, exogenous increase in PEA traffic and lead emissions, especially for children attending schools near airports after 2007.

We estimate the effects of piston-engine aircraft activity by employing a triple-differences design that leverages three sources of variation: cross-cohort variation in PEA traffic exposure generated by a sharp increase in PEA activity in Texas after 2007, cross-school variation in distance to airports, and cross-airport variation in the magnitude of the post-2007 increase in PEA operations. Our empirical model compares the post-2007 change in the outcome gap between students attending schools within one mile of an airport and schools one to three miles away around high-surge airports to the corresponding change in the close–far gap around airports with little or no increase in PEA activity. Our main sample consists of third-grade students attending Texas public schools within three miles of airports with PEA operations during 2005–2009. We measure short-run outcomes using standardized test scores, attendance, and behavioral outcomes. We examine longer-run outcomes including high school graduation, college enrollment, degree completion, and earnings at ages 22 and 23.

We find that exposure to high PEA activity adversely affects children's human capital accumulation. Third-grade reading scores fall by 0.168 standard deviations for

students attending schools within one mile of airports that experienced an increase of more than 2,000 PEA activities (on average: 4,166) from 2007 to 2008 relative to the triple-difference comparison group.[3] Third-grade math scores decrease by 0.065 standard deviations, although the estimate is statistically insignificant. These effects are not explained by selective test participation: we find no statistically significant effect on the probability of taking the standardized reading or math exams.

We also find evidence that exposure to high PEA activity affects long-run educational attainment. High school graduation falls by 4.5 percentage points, a 6% decrease relative to the control mean. We see a similar decrease in graduating from high school on time. Public university enrollment drops by 3.9 percentage points, a 25% decline relative to the control mean. On-time college enrollment declines by 4.6 percentage points, presenting an 11% decrease compared to the control mean. The likelihood of getting a college degree is also lower, although the estimated effects are statistically insignificant at conventional significance levels. Furthermore, exposure to high PEA activity is associated with lower earnings around age 22 and 23, although the estimates are imprecise and statistically insignificant. In contrast, we find limited evidence of effects on behavioral and attendance outcomes. The estimated effects on crime, violence, disciplinary incidents, and attendance are generally small and statistically insignificant.

Several robustness checks support the validity of the empirical design and strengthen the interpretation that the estimated effects reflect exposure to PEA activity and lead emissions. Event-study estimates show little evidence of differential pre-trends in test scores or longer-run educational outcomes before the increase in PEA activity. Balance checks show no statistically significant changes in school funding or observable student composition around high-surge airports after 2007. The estimated effects are also largest for schools closest to airports and attenuate with distance, consistent with prior evidence that children's BLLs decline dose-responsively with distance from airports (Miranda et al., 2011; Zahran et al., 2017). In addition, the reduction in educational attainment is mainly due to the emissions of lead from PEA, as evidenced by decreases in other pollutants such as $PM_{2.5}$ and spikes in lead concentration post-2007 near airports with PEA operation. Finally, the main educational effects are robust to alternative definitions of high PEA traffic and are not driven by a single grade cohort or demographic subgroup.

This paper contributes to three strands of literature. First, it contributes to the

[3] In Section 8, we use existing estimates of the relationship between PEA traffic and children's blood lead levels to benchmark these effects against the broader lead literature.

literature on lead exposure and human capital. A large body of medical and economic evidence shows that lead harms children's cognitive and behavioral development, with important consequences for schooling, crime, and adult outcomes (Needleman et al., 1979; Schwartz, 1994; Canfield et al., 2003; Lanphear et al., 2005; Reyes, 2007, 2015; Aizer et al., 2018; Aizer and Currie, 2019; Grönqvist et al., 2020; Gazze et al., 2024; Hollingsworth et al., 2025). Much of this evidence comes from settings with higher historical exposure levels or from legacy sources such as leaded gasoline, paint, and plumbing. Our setting examines a contemporary low-exposure environment, where average blood lead levels are far below historical levels, but localized emissions persist. The results show that even in this low-dose setting, lead exposure can have detectable effects on children's learning and educational trajectories.

Second, the paper contributes to the emerging literature on aviation gasoline and child lead exposure. Prior work shows that children living near airports with piston-engine aircraft have higher blood lead levels, and that exposure varies with proximity, wind direction, and airport activity (Miranda et al., 2011; Zahran et al., 2017, 2023; Soale et al., 2024; Berg et al., 2024). While this evidence establishes an important exposure pathway, it does not directly estimate the consequences for educational or economic outcomes. We extend this literature by providing new causal evidence of PEA activity on children's educational attainment, behavioral outcomes, and early labor market outcomes.

Third, the paper contributes to the broader literature on environmental quality and human capital accumulation. Prior research shows that air pollution affects worker productivity, cognitive performance, test scores, and later-life outcomes (Zivin and Neidell, 2012; Chang et al., 2016; Ebenstein et al., 2016; Lichter et al., 2017; Archsmith et al., 2018; Chang et al., 2019; Zivin et al., 2020; Behrer et al., 2026). We add to this literature by studying airborne lead, a pollutant with persistent neurotoxic effects, and by tracing impacts from elementary-school achievement to later educational and labor market outcomes.

Our findings have direct policy implications. Because piston-engine aircraft emissions are highly localized, the costs of leaded aviation fuel are borne disproportionately by children attending schools near high-activity airports. Our estimates imply that eliminating leaded aviation gasoline may generate benefits beyond reductions in measured blood lead, including improvements in reading achievement and educational attainment. More broadly, the results suggest that the human capital benefits of addressing remaining lead sources are meaningful even when aggregate exposure levels are low relative to historical standards.

The remainder of the paper proceeds as follows. Section 2 provides institutional background on lead exposure, leaded aviation gasoline, and the post-2007 increase in PEA activity. Section 3 describes the airport operations data and Texas administrative education and earnings data. Section 4 presents the empirical strategy. Section 5 reports the main results. Sections 6 and 7 present robustness checks and heterogeneity analyses. Section 8 discusses the magnitude of the estimates and policy implications, and Section 9 concludes.

2 Background

To motivate our empirical strategy, this section provides context on three dimensions. First, we review the health and developmental consequences of lead exposure, emphasizing why even low levels remain a policy concern. Second, we describe piston-engine aircraft (PEA) and their dependence on leaded aviation fuel, which has made them the largest remaining source of airborne lead in the U.S. Finally, we present evidence on the unusual surge in PEA operations during 2007–2009, which we exploit as a quasi-experimental shock to children's exposure.

2.1 Background of lead

Lead is a highly toxic metal that causes adverse health impacts once it enters the body. Historically, it was widely used in gasoline, paint, plumbing, and batteries (NIH, 2007). Tetraethyl lead (TEL), the additive once used in gasoline, is hazardous. When DuPont first opened its TEL plant in New Jersey in 1924, several workers died of acute poisoning, and more than 80 percent of Standard Oil workers exposed to TEL that year suffered severe illness or death (Kitman, 2000).

Lead can enter the body through inhalation, ingestion, or, less commonly, through the skin. Once absorbed, it circulates in the bloodstream and is deposited in soft tissues such as the brain and kidneys as well as in bones and teeth, where it can remain for decades. Although some lead is excreted over time—its half-life in blood is about 30 days and in soft tissue about 40 days—it can persist in bone for 10 years or longer. Due to this bioaccumulation, even low-level, chronic exposure can lead to long-term harm, and the adverse effects persist even after exposure ceases.

Children are especially vulnerable because they absorb more lead relative to body weight and because their nervous systems are still developing. Lead exposure damages nearly every organ system, with particularly pronounced effects on the brain and

central nervous system. Documented consequences include impaired kidney and cardiovascular function, reduced immune response, and developmental and reproductive problems. High levels of lead exposure have been linked to reduced IQ, diminished school performance, behavioral issues such as hyperactivity and attention deficits, and higher rates of delinquency and violent crime (EPA, 2013; Aizer and Currie, 2019).

Despite the success of U.S. policies in dramatically reducing lead emissions—an estimated 170 million Americans nonetheless experienced high exposure during childhood (McFarland et al., 2022)—lead remains a pressing public health concern. Recent evidence shows that one in two U.S. children under the age of six still has detectable blood lead levels (Hauptman et al., 2021). The Centers for Disease Control and Prevention (CDC) concludes that there is no safe level of exposure (CDC, 2012). Moreover, because lead cannot be destroyed in the environment and persists in human tissue for years, preventing emissions at the source is critical.

2.2 Background of leaded aviation fuel

The U.S. has taken significant steps to transition away from leaded fuels. In the 1970s, one of the largest sources of lead emissions in the U.S. was from automobiles. The U.S. Congress founded the U.S. Environmental Protection Agency (EPA) in 1970 and adopted the Clean Air Act, which set air quality standards (EIA, 2020). By 1975, all new cars were required to have catalytic converters that only used lead-free fuel (EPA, 1996). In 1976, the U.S. Environmental Protection Agency (EPA) initiated an effort to phase out leaded gasoline by mandating that gas stations offer unleaded gasoline. Over a decade after this deleading effort, the amount of lead used in automotive gasoline fell dramatically by 99 percent. Effective January 1, 1996, the EPA altogether banned leaded gasoline for on-road vehicles (EIA, 2020).

Piston-engine aircraft (PEA) are one of the few off-road vehicles that are still permitted to use leaded gasoline, known as aviation gasoline (avgas). PEA are small planes used by flight schools, businesses, and individuals for personal flying, training, sightseeing, recreation, and search and rescue. Avgas is the specialized fuel for PEA. TEL is added to avgas to raise fuel octane and prevent engine knock and other issues in high-performance engines. Jet aircraft and turbine-power do not use avgas but use lead-free fuels similar to kerosene (Federal Aviation Administration, 2019a).

Despite the recent discovery of unleaded avgas (Billing, 2014), leaded avgas remains the most used fuel for PEA. Today, the most common avgas in the U.S. market is 100 MON low lead (100LL). However, even the low-lead type of avgas still contains

up to 0.56 grams of lead per liter. This is equivalent to 2.12 grams of lead per gallon.

With the elimination of lead emissions from cars and trucks, PEA operating on avgas is the largest source of ambient lead concentration (AOPA, 2016). Around 70 percent of airborne lead emissions in the U.S. result from PEA operations (Santa Clara County, 2021). It is estimated that avgas is widely used in approximately 170,000 PEA in 20,000 airports across the U.S. (Federal Aviation Administration, 2019a).

Lead emissions from PEA pose a threat to public health and welfare. Sixteen million people live, and 3 million children attend school within 1km of an airport with piston-engine aircraft operating on avgas (EPA, 2010). Children living or attending school near airports can inhale airborne lead directly or ingest lead settled in soil or dust. Previous research by EPA (2010) and Illinois Environmental Protection Agency (2002) indicates that lead emissions from these small airplanes can negatively impact children's health, especially those who live or attend school near airports.

The lack of regulation of lead emissions from PEA raised concerns among policymakers, environmentalists, and non-profit organizations. In 2006, Friends of the Earth filed a petition requesting that the EPA initiate rulemaking to address general aviation lead emissions. Since then, several more community groups and non-profit organizations have continued to call for the EPA to take the necessary steps in regulating lead emissions from piston aircraft. Most recently, the county of Santa Clara in California and 39 organizations filed a petition urging the EPA to initiate a nationwide ban on leaded avgas (EarthJustice, 2021). In response to the growing concern over lead emissions from PEA, the EPA has been actively investigating whether lead emissions from PEA contribute to air pollution and pose a threat to society's welfare (EPA, 2015). In addition, the EPA has called for further research to provide evidence on the impacts of piston aircraft lead emissions on air quality and an analysis of the affected population.

2.3 Background of the surge in piston-engine aircraft activity after 2007

FAA operations data show a sharp and temporary increase in PEA activity in Texas after 2007. Figure 1 shows PEA activity rising beginning in 2007, peaking in 2008, and receding after 2009. Jet operations do not exhibit a comparable spike during the same time period, suggesting that the increase in aviation activity is specific to PEA operation. This distinction is central in our setting because PEA, unlike jet

aircraft, relied on leaded aviation gasoline.[4] The post-2007 change in the aviation industry therefore reflects an increase in lead-emitting aircraft activity rather than a broad expansion of airport activity in Texas. The timing of this PEA traffic spike provides a natural experiment of increased exposure to uncover causal evidence of PEA activity on children's non-health outcomes in the short and long run.

The timing of the PEA activity spike coincided with growing demand for pilots and increasing pressure to expand pilot-training capacity in the aviation sector. Federal Aviation Administration (2008b) documented an increase in general aviation flight hours starting in 2007 and noted that general aviation activity at towered airports rose for the first time since 1999. This evidence suggests a strong growth in the aviation sector in the post-2007 period. At the same time, industry forecasts described growing concerns about the shortage of pilot supply and industry efforts to attract new pilots. The Boeing Company (2006) projected substantial demand for new pilots over the following two decades: more than 17,000 new pilots per year from 2006 to 2025. However, according to the International Air Transport Association (2008), the projected pilot demand exceeded existing training capacity. As a result, during this time, regional airlines heavily adjusted hiring and training practices in response to staffing pressures and growing pilot demand (Phillips, 2007).

Because commercial pilot training is conducted largely in small piston-engine aircraft, increased training demand would translate directly into higher PEA operations. An instrument rating is a required step for professional pilots and comes after the private pilot license (Voss, 2008). Because it requires substantial additional training in PEA, a surge in instrument ratings indicates intensified pilot training activity. Figure 2 shows that PEA operations mirror the trend of the number of instrument-rated pilots. Both increased after 2007 and peaked in 2008 before declining thereafter, suggesting that the peak in PEA is driven by increased flight training to keep pace with higher demand in the aviation sector. Furthermore, training flights also generate repeated takeoffs, landings, and local-area operations, producing substantial airport-level PEA activity. Because PEAs relied on leaded aviation gasoline (100LL), increased PEA traffic due to training activity translated directly into increased local lead emissions.

Several independent data sources and industry reports further corroborate the

[4]The primary aviation gasoline used by piston-engine aircraft during this period was 100-octane low-lead gasoline, commonly known as 100LL. Although labeled "low lead," 100LL contains tetraethyl lead and is the main source of lead emissions from general aviation aircraft. Jet aircraft, by contrast, use turbine fuel and are not the source of lead emissions studied here (Federal Aviation Administration, 2019b).

underlying mechanism that the 2008 peak in PEA activity was driven by increased flight-training activity. Shetty and Hansman (2012) use FAA survey data to show that instructional flying hours reached their peak in 2008 after several years of decline following the September 11 attacks, further supporting the strong growth in the aviation sector in the post-2007 period.[5] Specifically, roughly one quarter of pilots reported that their peak flying activity occurred between 2005 and 2009, and nearly half of these pilots attributed the increase to training for pilot licenses or advanced ratings. Furthermore, there is a noticeable uptick in 2008 in the distribution of first years of flying, consistent with a wave of new entrants into flight training. Together with the fact that Texas was also among the leading states in pilot training activity,[6] where a good portion of pilots were based during this time,[7] these industry sources provide direct evidence that the PEA surge in 2008 was training-driven and geographically concentrated in states with high general aviation activities like Texas.

Additionally, the airport-level geography of the PEA increase in Texas further supports the flight training mechanism. Figure 3 shows the locations of flight schools and training centers as well as the change in PEA activity in 2008 compared to 2007. Figure 3 suggests that airports experiencing the largest increases in PEA operations are disproportionately located at FAA-identified flight-training facilities. This evidence suggests that the spike in PEA is not due to general airport growth, recreational flying, or local economic growth. In fact, since the surge was concentrated at airports with flight training infrastructure, it is more consistent with the explanation that the increased demand for pilot certification and advanced ratings translated into additional PEA traffic.

In conclusion, the timing, aircraft type, training evidence, and airport-level geography point to a temporary PEA activity shock that increased lead emissions near affected airports. Due to the increasing pilot demand, flight training activity rose sharply in 2008. Since flight training primarily used lead-emitted PEA, there is a peak in PEA activity during this time, particularly in a major pilot-training state such as Texas, resulting in higher local lead emissions near affected airports. Together, this evidence corroborates the underlying mechanism that increased PEA

[5] FAA general aviation surveys define instructional flying to include flights conducted under the supervision of a flight instructor, as well as student-pilot solo flights (Federal Aviation Administration, 2008a)

[6] According to Federal Aviation Administration (2026), Texas ranked among the top three states for both active pilots and instrument-rated pilots, accounting for approximately 9 percent of all U.S. pilots and 13 percent of instrument ratings.

[7] More than 10% of pilots reported their primary base in their peak training year to be Texas (Shetty and Hansman, 2012)

activity post-2007 would be driven by increased flight training and helps rule out that this peak is due to a general airport-traffic shock or driven by local economic conditions. Moreover, this evidence reveals helpful variation in terms of timing, exposure intensity, and geographic location for our analysis. This institutional setting motivates our empirical design described in Section 4.

3 Data

In this section, we describe main data sources used in this paper. We combine PEA operational data with educational and labor market outcome data to build an longitudinal individual-level dataset linking PEA activity to short- and long-term outcomes.

3.1 Piston-Engine Aircraft Operation Data

We collected PEA operation data from the Federal Aviation Administration (FAA) Traffic Flow Management Systems Counts (TFMSC). The TFMSC database provides daily traffic count data by airport and aircraft type and collects flight data through pilot flight plans and the National Airspace System (NAS) through RADAR. The TFMSC data are available from January 2000 to the present and are updated monthly.

We aggregate the data to have annual operation counts for PEA and other lead-free aircraft for every airport in Texas between 2000 and 2025. Total operations are defined as the sum of departures and arrivals. TFMSC reported total piston-engine aircraft operations for over 180 airports during this period. However, in the main analyses, we will only use data from 157 airports with PEA traffic counts available from 2000 to 2010. We combined PEA operations at Texas airports with information on these airports' locations (such as longitude and latitude) collected from the Aircraft Owner and Pilot Association (AOPA) and confirmed with the Texas Airport Directory by the Texas Department of Transportation.

Figure 1 shows the annual PEA and JET operations in Texas between 2000 and 2024. The PEA operation in Texas gradually fell in the years that followed the 9/11 attacks. However, due to increased instructional training, PEA operations surged between 2008 and 2009.

3.2 Longitudinal Student Level Data

We have access to educational and earnings data through the Texas Education Research Center (ERC), which maintains the administrative data for each student at-

tending Texas public schools. Specifically, the Texas ERC compiles pre-kindergarten through the twelfth grade (PK-12) educational records from the Texas Education Agency (TEA), the post-secondary education records within Texas from the Texas Higher Education Coordinating Board (THECB), the post-secondary education records from other states via the National Student Clearinghouse (NSC), and the Texas employment earnings data from the Texas Workforce Commission (TWC). Each dataset includes a unique identifier that serves as a substitute for Social Security Numbers, enabling longitudinal tracking of a student across these diverse datasets. Brief introductions to each dataset and definitions of key outcome variables used in this study are provided below.

3.2.1 TEA 2000-2024

Reading and math scores are important measurements of educational performance. These test score data come from the Texas standardized assessment, the Texas Assessment of Knowledge and Skills (TAKS). The TAKS was administered from 2003 to 2011. Students in grades 3 to 11 are required to assess their reading and math skills, with raw scores reflecting the number of correctly answered multiple-choice questions. In this paper, we standardize test scores by year, grade, and subject, with a mean of zero and a standard deviation of one.

High school graduation is another critical measure of educational achievement. In this study, we define "ever graduating from high school" as ever obtaining a high school diploma (excluding a GED). Additionally, we categorize high school graduation based on its timing relative to the expected schedule. For example, graduating on time means graduating from high school in 9 years after third grade.

In addition to educational attainment, we also investigate the effect of PEA activity on students' behavioral outcomes. The TEA includes data on the percentage of days of school attendance, disciplinary incidents, violent behavior, and criminal activity. This paper uses these variables to estimate the impact of increased PEA-related lead exposure on behavioral outcomes.

3.2.2 THECB 2010-2021 and NSC 2011-2019

Using the longitudinal data, we can track the effect on college enrollment outcomes both within and outside Texas. Specifically, the post-secondary outcomes are combined from THECB and NSC, including college enrollment and the types of institutions attended. We have developed two metrics for college enrollment: one tracking

enrollment from 2010 to 2021 and another assessing on-time enrollment, which we define as enrollment in college 9 years after third grade.

3.2.3 TWC Wages Data 2007-2024

The Texas Workforce Commission provides most wage data earned within Texas. In the dataset, missing earnings records include individuals who are outside the labor force, unemployed, self-employed, or employed outside Texas. This study uses the same dataset as Zhong (2026), which documents that labor force disengagement, rather than data attrition, accounts for most missing wage observations among young adults in Texas. Specifically, the U.S. Census Bureau (2023) reports that approximately 35% of Texans over age 16 are out of the labor force, a pattern that is more pronounced among young adults and likely explains much of the missing wage data for individuals aged 23–26 in this setting. By contrast, unemployment (around 3% in Texas), self-employment (1.9% among young adults nationally, per Hipple and Hammond (2016)), and out-of-state employment (only 1.8% of Texans relocated and paid taxes elsewhere in 2021–22, per Internal Revenue Service (2022)) each account for a comparatively small share. Following Zhong (2026), this study codes missing wage records as zero to reflect labor market disengagement.

The outcomes of interest are annual earnings (missing values are coded as zero) at ages 22 and 23, which are the oldest ages we can observe for the main sample using earnings data up to 2024. We also generate variables indicating whether there are any earnings to reflect labor force participation.

3.3 Summary Statistics

This study's primary sample consists of third-graders from the 2005-06 to the 2009-10 school years, with earnings observed at least at age 23 for all cohorts. We further restrict the sample to students who attend schools within 3 miles of airports with PEA operations.

Table 1 summarizes airport characteristics separately for airports with a change in PEA of 25 or fewer (control airports) and for airports with a change in PEA greater than 2,000 (treatment airports) between 2007 and 2008. The two groups differ sharply in the change in PEA activity around 2008. Treatment airports experienced an average increase of 4,157 PEA operations between 2007 and 2008, whereas activity at control airports was essentially unchanged, declining by about 9 operations. Treatment airports were also substantially more active prior to the surge, averaging 6,211

PEA operations in 2007 compared with 246 at control airports, and this gap widened further in 2008. Consistent with PEA activity generating local lead exposure, average airborne lead concentrations measured near treatment airports are considerably higher than those near control airports (5.99 versus 0.71 μg/m^3), with the difference statistically significant at the 10 percent level. In contrast, $PM_{2.5}$ concentrations are similar between the two groups and not statistically significant. These summary statistics highlight both the large treatment-control contrast in PEA activity and the corresponding difference in airborne lead exposure, while providing little evidence of a comparable difference in other pollutants such as $PM_{2.5}$.

Table 2 reports summary statistics for students attending schools located in the four groups that define the triple-differences design: schools within one mile of high-surge airports, schools one to three miles from high-surge airports, schools within one mile of low-surge airports, and schools one to three miles from low-surge airports. The table shows that schools and students differ along both dimensions of treatment variation: distance to the airport and the magnitude of the post-2007 change in PEA activity. Among high-surge airports, students attending schools within one mile are more likely to be Hispanic, bilingual, and eligible for free meals than students attending schools one to three miles away. Among low-surge airports, schools also differ from the one- to three-mile comparison group in racial and socioeconomic composition. These descriptive patterns indicate that schools closer to airports are not directly comparable to those farther away in terms of levels.

The table also shows that high- and low-surge airport areas differ in outcome levels. Students near high-surge airports tend to have higher long-run educational attainment and earnings than students near low-surge airports, particularly among schools located one to three miles from the airport. At the same time, schools located closer to airports often have lower contemporaneous academic outcomes than schools farther away, including lower reading scores and higher rates of test non-participation in several groups. These differences underscore that neither a cross-sectional close-far comparison nor a simple comparison between high- and low-surge airport areas would provide a credible estimate of the effect of aviation lead exposure.

The preferred triple-differences design compares the post-2007 change in the close-far outcome gap around high-surge airports to the corresponding change in the close-far gap around low-surge airports. The level differences documented in Table 2 motivate the inclusion of school fixed effects and student-level controls in the main specification and highlight the importance of the pre-trend and compositional stability checks presented below.

4 Empirical Strategy

To estimate the effect of increased exposure to lead emissions from piston-engine aircraft, we use a triple-differences design that combines variation across time, distance to airports, and the magnitude of changes in PEA activity. The empirical challenge is that PEA activity increased after 2007, during a period when other economic and policy changes may also have affected student outcomes. A simple comparison of schools near airports before and after 2007 could therefore confound the effect of aviation lead exposure with broader changes affecting airport-adjacent areas. Similarly, a difference-in-differences comparison of schools closer to airports with high surge PEA activity and schools with low PEA activity could be biased if high-surge schools were differentially affected by other post-2007 shocks.

We address this concern by comparing how the close–far difference in student outcomes changes after 2007 around airports that experienced large increases in PEA operations to the corresponding change in the close–far difference around airports with little or no change in PEA activity. This triple-differences design is our preferred empirical specification. The first difference compares outcomes before and after the post-2007 increase in PEA activity. The second difference compares schools very close to airports with those slightly farther away. The third difference compares airports with large increases in PEA operations to airports with little or no change.

Intuitively, if increased aviation lead exposure is the relevant mechanism, the post-2007 divergence in outcomes between close and comparison schools should be concentrated around airports where PEA operations increased substantially. In contrast, around airports with little change in PEA activity, close and comparison schools should exhibit more similar changes in outcomes. This design therefore differences out shocks common to close and comparison schools near the same type of pollution source, as well as changes over time that are common to high- and low-surge airport areas.

The remaining threat to identification is the presence of other contemporaneous shocks that differentially affected schools very close to airports relative to those slightly farther away, particularly in areas where PEA activity increased substantially. To alleviate this concern, we implement several strategies. First, we include rich student-level controls and school fixed effects to absorb observable and time-invariant differences. Second, we restrict the comparison group to schools located within a narrow geographic band around airports to enhance local comparability. Finally, we conduct event-study analyses to test for differential pre-trends and exam-

ine whether observable school resources and student composition change differentially across groups. Together, these approaches strengthen the credibility of the identifying assumption.

We estimate the following specification:

$$\begin{aligned} Y_{ist} = \beta_0 &+ \gamma_1\big(\text{close}_{as} \times \text{post}_t\big) + \gamma_2\big(\text{close}_{as} \times \text{treatgroup}_a\big) \\ &+ \gamma_3\big(\text{post}_t \times \text{treatgroup}_a\big) + \gamma_4\big(\text{close}_{as} \times \text{post}_t \times \text{treatgroup}_a\big) \\ &+ \gamma_5 \text{close}_{as} + X_{ist} + \delta_s + \theta_t + \varepsilon_{ist}. \end{aligned} \tag{1}$$

Here, Y_{ist} denotes the outcome of third-grade student (i) attending school (s) in year (t), and (a) denotes the airport closest to school (s).[8] The variable close_{as} is an indicator equal to one if school (s) is located within one mile of airport (a), and zero if it is located between one and three miles from the airport. The indicator post_t equals one for years 2008 and after, capturing the period of elevated PEA activity documented in Section 2, and zero for years 2005 through 2007. The variable treatgroup_a indicates airports that experienced a large post-2007 increase in PEA operations. In the main specification, treated airports are defined as those with more than 2,000 additional PEA operations, while comparison airports are those with changes of 25 operations or less.

The coefficient of interest is γ_4, the coefficient on the triple interaction between close_{as}, post_t, and treatgroup_a. This coefficient measures whether the post-2007 change in outcomes for schools within one mile of an airport, relative to schools located one to three miles away, differs between airports with large increases in PEA operations and those with little or no change. Equivalently, γ_4 identifies the change in the close-far outcome gap after 2007 at high-surge airports relative to the corresponding change in the close-far gap at low-surge airports.

The vector X_{ist} includes student-level controls for eligibility for free meals, gender, race and ethnicity, and bilingual status. The specification includes school fixed effects, δ_s, which absorb time-invariant differences across schools, including permanent differences in neighborhood characteristics, baseline school quality, proximity to the airport, and assigned-airport characteristics that do not vary over time. Year fixed effects, θ_t, absorb shocks to student outcomes that are common across schools in a given year, including statewide policy changes and macroeconomic shocks. Standard errors are clustered at the school level.

[8] Our main analyses focus on third-grade students because third grade is the earliest grade for which test scores are available. For the heterogeneity analyses, we expand the sample to include students in grades 3 through 5.

The identifying assumption is that, absent the post-2007 increase in PEA activity, the close-far difference in student outcomes would have evolved similarly around high- and low-surge airports. The remaining threat to identification is that some other contemporaneous shock differentially affected schools very close to airports, relative to schools slightly farther away, specifically in areas where PEA activity increased substantially. We address this concern in several ways. First, in the main specification, we include student-level controls and school fixed effects to absorb observable and time-invariant differences across schools. Second, we restrict the main estimation sample to students attending schools within three miles of airports with PEA operations during the study period. The comparison group therefore consists of schools near airports, but at somewhat greater distances from the emissions source. This restriction improves comparability by focusing on schools located in geographically proximate areas that are likely to share similar local economic conditions, school district environments, and exposure to airport-related amenities or disamenities other than lead emissions, while preserving meaningful variation in exposure to emissions from PEA activity. Finally, we assess the plausibility of the identifying assumption directly using event-study analyses that test for differential pre-trends and balance checks that examine whether school resources or observable student composition change differentially across treatment groups.

We assess the plausibility of the triple-differences identifying assumption in two ways. First, we estimate event-study versions of the main specification. These models replace the post-period treatment interaction with year-specific interactions between the close-school indicator, the high-surge airport indicator, and year indicators, normalizing 2008 to zero. The pre-2008 coefficients therefore test whether the close-far gap in outcomes was already evolving differentially between high-surge and low-surge airports before the increase in PEA activity. Figure 4 presents the event-study estimates for third-grade reading and math scores. The pre-period coefficients are close to zero and statistically indistinguishable from zero for both outcomes, providing little evidence of differential pre-trends in the main short-run academic outcomes. Figures 5 and 6 report analogous event studies for longer-run educational and earnings outcomes. These estimates similarly show no systematic evidence of differential pre-trends, although the earnings estimates are less precise. Overall, the event-study evidence supports the identifying assumption that, absent the increase in PEA activity, the close-far outcome gap would have evolved similarly around high- and low-surge airports.

Second, we examine whether the increase in PEA activity coincides with changes

in school resources or observable student composition. Table 3 presents the estimated results from the main triple-differences specification, with school funding and student demographic characteristics as outcomes. Across all columns, the estimated coefficients are statistically insignificant. The estimated effect on school funding is positive but not statistically significant, indicating no clear evidence that schools near high-surge airports experienced different changes in resources after 2007. Similarly, we find no statistically significant changes in the shares of students eligible for free meals, female students, racial and ethnic composition, or bilingual students. These results suggest that the main estimates are unlikely to be driven by differential changes in observable student composition or school funding around high-surge airports. In other words, the balance test provides no evidence of systematic sorting or resource changes coinciding with the increase in PEA activity.

5 Main Results

5.1 Educational Outcomes

Table 4 reports the main triple-differences estimates for educational outcomes. Column 1 shows that an increase of 4,166 PEA activity per year leads to a statistically significant decline in third-grade reading scores.[9] The estimated coefficient is -0.168 standard deviations, which is a 141% decrease compared to the control mean, indicating that the post-2007 close-far gap in reading scores worsened substantially around high-surge airports relative to low-surge airports. The estimate for math scores in column 2 is -.065, a 53% decrease relative to the control mean, though the estimate is statistically insignificant. Equivalently, a one-unit increase in airborne lead ($\mu g/m^3$) reduces third-grade reading and math scores by 0.040 and 0.016 standard deviations, respectively.[10] By applying an air-to-blood ratio of 2 μg/dL for every 1 μg/m^3, which aligns with EPA assessments on the relationship between airborne lead and children's blood lead levels, we find an implied effect of about -0.02 and -0.008 standard deviations on reading and math scores for each 1 μg/dL increase in BLLs. (U.S. Environmental Protection Agency, 1977, 1986)

[9] Table 1 shows PEA traffic increases by 4,166 flights in 2008 relative to 2007 for the treatment group compared to the control group.

[10] Figure A2 shows that an increase of 1 PEA activity increases lead by 0.001 $\mu g/m^3$. Table 1 shows PEA traffic increases by 4,166 flights for the treatment airports compared to the control airports. So, an increase of one unit of lead ($\mu g/m^3$) reduces reading scores by $(0.168sd/(4166 * 0.001) = 0.04sd)$.

Columns 3 through 8 examine longer-run educational outcomes. We find a statistically significant 4.5 percentage-point decline in high school graduation, a 6% decrease relative to the control mean. Equivalently, a one-unit increase in BLLs (μg/dL) reduces high school graduation by 0.54 percentage points. We also find a statistically significant 3.9 percentage point decline in public university enrollment, a 25% decline relative to the control mean. This is equivalent to a 0.47 percentage point reduction in public university enrollment per one-unit increase in BLLs (μg/dL). The estimate for any college enrollment is negative but not statistically significant, while the estimated coefficient for community college enrollment is close to zero. The degree-completion estimates are negative but imprecise. These results suggest that increased exposure to PEA activity has detectable effects on some margins of educational attainment, particularly high school completion and public university enrollment. However, the evidence is weaker for overall college enrollment and degree completion.

Figures 4 and 5 present event-study estimates corresponding to the main educational outcomes. Consistent with the identifying assumption, the pre-2008 coefficients are generally close to zero and statistically indistinguishable from zero. After 2007, the reading estimates move in the expected negative direction, with larger negative effects appearing in 2008 and 2009. The math estimates are less precise and do not show the same clear pattern. For longer-run outcomes, the pre-trends in the event study figures are largely flat and statistically indistinguishable from zero. Additionally, the post-period estimates for public university enrollment are negative, consistent with the corresponding estimate in Table 4.

Table 5 examines test participation and on-time educational progression. Columns 1 and 2 show no statistically significant effects on test non-participation. The estimate for not taking the reading test is close to zero, suggesting that the negative reading-score effect is not driven by selective test-taking. The estimate for not taking the math test is positive but imprecise.

Columns 3 through 6 show that increased PEA activity reduces timely progression through the education system. The estimated effect on on-time high school graduation is -4.2 percentage points, a 6.7% decrease relative to the control mean. On-time college enrollment falls by 4.6 percentage points (an 11% decrease compared to the control mean), and on-time public university enrollment falls by 4.1 percentage points (a 36% decline compared to the control mean). The estimate for on-time community college enrollment is negative but statistically insignificant. Equivalently, for a one-unit increase in BLLs (μg/dL), on-time high school graduation and college enrollment reduce by 0.51 and 0.55 percentage points, respectively. These results indicate

that the effects of increased PEA exposure extend beyond contemporaneous test performance and are reflected in delayed or reduced progression into later educational milestones, particularly high school completion and public university enrollment.

5.2 Behavioral Outcomes

Table 6 examines whether increased PEA activity affects behavioral outcomes. Overall, we find little evidence of adverse behavioral effects. The estimated effects on total crime, total violence, total disciplinary incidents, and indicators for any crime or any violent incident are small and statistically insignificant. The estimate for any disciplinary incident is statistically significant but negative, indicating a decline rather than an increase in disciplinary involvement. Because this estimate goes in the opposite direction of an adverse behavioral response and is not accompanied by a statistically significant decline in total disciplinary incidents, we do not interpret it as evidence of a meaningful behavioral effect. The attendance estimate is also negative but statistically insignificant. The results suggest that the effects of increased PEA exposure are concentrated in academic achievement and educational progression, with little evidence of corresponding impacts on behavioral outcomes or attendance.

The absence of detectable behavioral effects in our study differs from a well-established literature linking high levels of lead exposure to delinquency, crime, and behavioral problems (Reyes, 2015; Aizer and Currie, 2019; Grönqvist et al., 2020). We attribute this difference to variations in exposure level and in statistical power rather than evidence against a behavioral channel. Previous studies identify effects from chronic, early-childhood exposure at higher levels. For instance, Grönqvist et al. (2020) find behavioral and criminal effects emerging around and above 5 μg/dL, drawing on samples of hundreds of thousands of children. In contrast, our study examines a transient surge in ambient exposure on a low baseline of 1.3–1.8 μg/dL.[11] Moreover, behavioral and criminal outcomes are infrequent in our sample. Less than 10% of students have any recorded crime, making it difficult to detect economically significant effects. Therefore, the results suggest that the short-term consequences of this low-level exposure primarily affect academic achievement, while not ruling out potential behavioral effects of sustained or higher exposure.

[11] We have more details in Section 8.

5.3 Early-Career Earnings

Table 7 reports estimates for early-career earnings outcomes measured at ages 22 and 23. The estimated effects for annual earnings are negative at both ages, but small relative to the control means and statistically insignificant. Specifically, at age 22, the estimate suggests a decrease of \$495, which represents a 3% decline relative to a control mean of \$13,933. At age 23, the estimate reflects a decrease of \$140, corresponding to 0.8% relative to a control mean of \$15,631.

In contrast, we find a statistically significant temporary reduction in labor market participation. At age 22, the probability of having any earnings declines by 5 percentage points, representing an 8% decrease relative to a control mean of 63%. The estimate at age 23 is smaller and statistically insignificant. The event-study estimates in Figure 5 are consistent with this overall pattern, suggesting that the earnings estimates are noisy and do not display a systematic negative trend following 2007. In summary, the results suggest some evidence of reduced labor-market performance at age 22, but little evidence of persistent earnings losses by age 23.

We interpret these early-career earnings results with caution because the treatment affects educational progression before students are fully involved in the labor market. As shown above, increased PEA activity reduces (on-time) high-school completion and (on-time) college enrollment. These adverse educational impacts can influence earnings at ages 22 and 23 through two competing channels. On one hand, lower academic achievement and reduced high school completion may decrease employment and earnings. On the other hand, lower college enrollment may move some marginal students into the labor market earlier than they otherwise would, increasing measured earnings at these ages relative to students who remain enrolled. The earnings estimates therefore reflect a combination of effects on human capital, employment, and the timing of schooling, rather than isolating long-run productivity in the labor market.

This timing also distinguishes our estimates from prior evidence on the labor market effects of lead exposure. Grönqvist et al. (2020) finds a negative effect on earnings in later adulthood. In contrast, we measure earnings outcomes only at ages 22 and 23, when many individuals are still enrolled in college or just beginning to enter the labor market. This difference may also reflect variations in dose: Grönqvist et al. (2020) measures the impact of heavy lead exposure from gasoline, whereas this paper focuses on low-level exposure from PEA in a contemporary setting. Consequently, we interpret the early-career earnings estimates as limited evidence on labor market consequences, rather than as evidence that such consequences are absent.

6 Robustness Checks

6.1 Spatial Gradient

Figure 7 examines whether the estimated effects vary with distance to the airport. For each outcome, we re-estimate the triple-differences specification using alternative distance bands as the treatment group and schools located two miles farther away as the corresponding comparison group. This exercise provides a test of the spatial gradient implied by aviation lead exposure. If lead emissions from PEA activity are the relevant mechanism, the effects should be largest for students attending schools closest to airports and should attenuate as the treatment group moves farther from the emissions source.

The results are consistent with this prediction. For reading scores, the estimated effect is largest and most negative for schools within one mile of an airport and becomes substantially smaller at farther distance bands. A similar, though less precise, pattern appears for math scores. The long-run educational outcomes show the same general gradient: the estimated effects on high school graduation, any college enrollment, and public university enrollment are most negative for the closest schools and attenuate toward zero as distance increases. In contrast, annual earnings at age 23 show no clear distance gradient, consistent with the main results showing limited evidence of effects on early-career earnings. Overall, the spatial pattern supports the interpretation that the estimated educational effects are driven by localized exposure to aviation lead emissions rather than broader shocks affecting airport-adjacent communities.

6.2 Alternative Definitions of High PEA Traffic

Figure 8 estimates the triple-differences specification separately across mutually exclusive bins of post-2007 changes in PEA operations. This tests whether the estimated effects vary with the magnitude of the increase in PEA activity. The reading-score estimates are negative across all traffic-intensity bins, suggesting that the short-run academic effects are not driven exclusively by the highest-surge airports. The estimates for high school graduation and any college enrollment are also generally negative across several intensity groups. We observe a slightly larger effect for the bin with PEA activity changes greater than 2,000, though the difference across bins is not statistically distinguishable from zero. The math-score estimates are smaller and less precise, while annual earnings at age 23 show no clear pattern across intensity

bins. Thus, Figure 8 provides suggestive evidence that the educational effects appear across a range of airports experiencing increases in PEA activity. However, it does not provide strong evidence of a monotonic dose-response relationship.

Figure 9 instead tests whether the main results are sensitive to the cutoff used to define the high-PEA treatment group. In each specification, the treated group is redefined using a different threshold for the post-2007 increase in PEA operations, while the comparison group is held fixed at airports with changes of 25 or fewer operations. The estimates of reading scores remain negative for all treatment cutoffs, indicating that the effect on short-term academic outcomes is not driven by the preferred threshold of more than 2,000 operations. The estimates for high school graduation, any college enrollment, and public university enrollment are also generally negative across alternative treatment definitions, though less precisely estimated at some cutoffs. In contrast, math-score estimates remain smaller and imprecise, and annual earnings at age 23 remain close to zero across cutoffs. Overall, these results show that the main educational findings are robust to alternative definitions of high PEA traffic, while the null earnings result is also stable across treatment definitions.

7 Heterogeneity Effects

Figure 10 examines heterogeneity by grade at exposure. We estimate the triple-differences specification separately for students exposed during grades 3, 4, and 5. This exercise assesses whether the main effects are specific to the third-grade sample or whether similar patterns appear for students exposed at adjacent stages of elementary school. The test-score estimates are negative across grades for both reading and math, indicating that the short-run academic effects are not limited to a single grade cohort. The estimates for high school graduation are also generally negative across grades. For longer-run outcomes, the pattern is less uniform: public university and any college enrollment decline for students exposed in grade 3, but not for students exposed in grades 4 and 5. Additionally, grade 5 exposure has a negative, statistically significant effect on annual earnings at age 23; grade 3 and 4 exposure does not. However, the differences in the estimated effect on college enrollment and earnings outcomes across grades are not statistically distinguishable from zero.

Figure 11 examines heterogeneity in the estimated effects across student subgroups defined by gender, race and ethnicity, free-meal eligibility, and bilingual status. The estimates are obtained from separate triple-differences regressions for each subgroup. Across educational outcomes, the point estimates are negative for several demographic

groups, suggesting that the adverse effects are not concentrated within any single subgroup. For reading scores, the negative estimates are particularly apparent among black and male students. The estimates for high school graduation and college enrollment are also generally negative across multiple subgroups, with some evidence of larger effects among economically disadvantaged students.

At the same time, the confidence intervals overlap substantially across groups, so we do not interpret the figure as evidence of statistically significant differences in treatment effects across subgroups. Rather, the results suggest that the main educational effects are broadly present across student groups, with suggestive evidence of larger impacts among some disadvantaged populations. The earnings estimates remain imprecise and do not show a consistent pattern across subgroups, consistent with the main results showing limited evidence of effects on early-career labor market outcomes.

8 Discussion

Evidence on the Lead Exposure Channel: Lead emissions from PEA traffic are the most plausible channel linking the post-2007 traffic surge to adverse student outcomes. The underlying shock in 2008 is specific to piston-engine aircraft rather than airport traffic in general. As shown in Figure 1, PEA traffic, which relies on leaded aviation gasoline, spikes in 2008, while jet traffic, which does not depend on leaded fuel, does not display a comparable increase. Furthermore, Figure A2 shows that increases in PEA traffic are associated with a statistically significant rise in airborne lead concentration. More importantly, Table 1 shows that schools in the treatment group are exposed to significantly higher levels of airborne lead than schools in the control group. This evidence therefore suggests that the PEA activity spike is a shock to lead exposure levels rather than a broad increase in airport activity, especially for those nearby airports with high PEA intensity.

In addition, we find little evidence that broader changes in airport-related air pollution such as PM2.5 drive the estimated effects. Several pieces of evidence suggest that the treatment is strongly related to lead exposure but not to PM2.5 exposure. Figure A1 compares annual PEA activity with airborne lead concentration and PM2.5 near airports. Airborne lead concentration closely tracks annual PEA traffic, whereas PM2.5 does not follow the PEA traffic trend and instead declines after 2007. The summary statistics in Table 1 point to the same conclusion. Treatment and control groups differ significantly in airborne lead exposure but not in PM2.5 levels. This

evidence further supports lead emissions from PEA, rather than other pollutants such as PM2.5, as the primary driver of adverse student outcomes.

The spatial pattern of the estimates further supports a localized lead exposure mechanism rather than broader changes in airport neighborhoods or school environments. Figure 7 shows that the effects of PEA's lead emissions are largest for schools within 1 mile of airports, smaller for schools 1-3 miles, and close to zero farther from the airports. This is consistent with localized lead exposure from repeated takeoffs, landings, and training operations near airports. As shown above, this is less consistent with explanations based on more spatially diffuse pollutants such as PM2.5. In addition, the event-study estimates in Figures 4-6 show no evidence of differential pre-trend across outcomes, and Table 3 shows that the increase in PEA is not systematically associated with changes in school funding or student composition. This evidence further confirms localized lead exposure from PEA traffic as the underlying mechanism rather than other aircraft types, other pollutants, or other social composition changes.

Lead Exposure at Contemporary Low Levels: This paper estimates the effects of lead exposure in a low-dose environment that is closer to contemporary conditions in the U.S. than the higher-exposure settings studied in much of the prior work. Since our administrative data do not include individual measurements of blood lead levels, we use external evidence to benchmark the exposure levels from PEA emissions during the study period. The closest benchmark comes from Zahran et al. (2023), who study children living within 1.5 miles of a PEA airport and report a mean BLL of 1.80 μg/dL. The National Health and Nutrition Examination Survey (NHANES) estimates for young children during 2007-2010 are lower at 1.3 μg/dL (CDC, 2013). Together, these two benchmarks suggest that the exposure levels in our study sample are likely in the low single digits, between 1.3 and 1.8 μg/dL. This differs from much of the existing evidence in the literature. Specifically, the pooled sample in Crawfurd et al. (2025) has an average blood lead level of about 7.06 μg/dL, whereas Aizer et al. (2018) studied Rhode Island children with a geometric mean of 3.1 μg/dL. Therefore, our setting differs from previous studies of high exposure levels and speaks more directly to the current environment, in which average BLLs have declined substantially and reached a historically low level.

Comparison to Prior Blood Lead Level (BLL) Estimate: To further understand the magnitude of our estimated effects on test scores, we compare our estimates

to prior causal evidence from settings with relatively low blood-lead levels (BLLs) and measured achievement outcomes. Aizer et al. (2018) provide a useful benchmark because they study children with blood-lead levels closer to the contemporary exposure range than much of the historical lead literature. Their paper estimates the effect of measured BLLs on test performance using an instrumental variables (IV) strategy and finds that a one μg/dL increase in BLLs reduces reading scores by 0.436 points. Since the standard deviation for reading scores in their sample is approximately 13, this corresponds to roughly -0.03 standard deviations per one μg/dL increase in BLLs. Their estimated effect on reading score would be a close benchmark for assessing whether the magnitude of our reduced-form effect is plausible.

Our calibrated estimate closely aligns with the preferred estimate from Aizer et al. (2018), reinforcing the reliability of our findings. As discussed, our reading estimate indicates an effect of approximately -0.04 standard deviations per additional 1 $\mu g/m^3$ of airborne lead. By applying an air-to-blood ratio of 2 μg/dL for every 1 $\mu g/m^3$, which aligns with EPA assessments on the relationship between airborne lead and children's blood lead levels, we find an implied effect of about -0.02 standard deviations for each 1 μg/dL increase in BLLs (U.S. Environmental Protection Agency, 1977, 1986). This effect size is slightly smaller but broadly comparable to the IV estimate in Aizer et al. (2018). This is consistent with our setting, where the contemporaneous exposure environment reaches a historically low level, and lead exposure from the PEA traffic spike is localized and transient.

Comparison to Educational Inputs: The estimated reading effect is also meaningful when compared with commonly studied educational inputs. A reduction of airborne lead by 1 $\mu g/m^3$ corresponds to an increase in reading achievement of approximately 0.04 standard deviations in our study. This is about one-fifth of the achievement gain associated with a one-standard-deviation improvement in teacher value added for one year, using estimates from Hanushek and Rivkin (2010) and Chetty et al. (2014). Additionally, it is comparable to the achievement gain from reducing class size by roughly three students under the Project STAR study (Krueger, 1999). Finally, using estimates from Jackson and Mackevicius (2024), the impact is of similar magnitude to the test-score gain from raising per-pupil spending by roughly \$1,250 over four years. These comparisons highlight that the educational costs of localized airborne lead exposure are quantitatively significant.

Policy Implications for Leaded Aviation Fuel: Our findings speak directly to

ongoing federal efforts to regulate lead emissions from piston-engine aircraft (PEA). U.S. Environmental Protection Agency (2023) issued a final endangerment finding concluding that lead emissions from PEA contribute to air pollution that endangers public health. This finding grants the EPA the authority to regulate these emissions under the Clean Air Act. At the same time, Federal Aviation Administration (2025) launched its EAGLE initiative to eliminate leaded aviation fuel by 2030. While it is well known that PEA remains the largest source of airborne lead emissions in the U.S., there is limited direct causal evidence on the impact of this source on human capital accumulation to inform policy interventions.

Our evidence contributes to this policy debate by showing that the costs associated with leaded aviation gasoline are highly localized rather than evenly distributed. Although average airborne lead emissions and children's BLLs are significantly lower than historical levels, children attending schools near high-activity airports continue to face considerable risks. These harms include not only short-term health and academic performance but also later educational progression and future earnings. These risks affect not only short-term health and academic performance but also later educational attainment and future earnings. This suggests that reducing or eliminating aviation-related lead emissions could enhance human capital accumulation.

9 Conclusion

Despite the dramatic decline in lead exposure following the phase-out of leaded gasoline for on-road vehicles, leaded aviation gasoline remains an important source of airborne lead emissions in the United States. This paper studies whether this low-level remaining source of lead exposure affects children's human capital development. We provide the first causal evidence on the effects of piston-engine aircraft (PEA) activity on both short-run academic outcomes and longer-run educational and labor market outcomes.

Our empirical strategy exploits a sharp increase in PEA activity in Texas after 2007, cross-school variation in distance to airports, and cross-airport variation in the magnitude of the post-2007 increase in PEA operations. The triple-differences design compares the post-2007 change in the outcome gap between students attending schools within one mile of an airport and schools one to three miles away around high-surge airports to the corresponding change in the close–far gap around airports with little or no increase in PEA activity. Event-study estimates provide little evidence of differential pre-trends, and balance checks show no systematic changes in observable

student composition or school resources following the increase in PEA activity.

The results show that increased PEA activity reduces third-grade reading achievement by 0.168 standard deviations (equivalent to a 0.02 standard deviation reduction for every μg/dL increase in BLLs), with smaller and statistically insignificant effects on math scores. We also find evidence that exposure affects later educational progression: high school graduation, public university enrollment, on-time college enrollment, and college completion all decline. Specifically, for each μg/dL increase in BLLs, high school graduation falls by 0.54 percentage points. Moreover, an increase of BLLs by one μg/dL reduces public university enrollment and on-time college enrollment by 0.47 and 0.55 percentage points, respectively. These effects are largest for schools closest to airports and attenuate with distance, consistent with a localized pollution-exposure mechanism. Additionally, high PEA activity is also associated with lower early career labor force participation, though the estimates are imprecise. In contrast, we find limited evidence of effects on behavioral outcomes and attendance.

These findings have two broader implications. First, they show that low-level lead exposure remains consequential even in a post-deleading environment. Although average blood-lead levels are now far below their historical peaks, remaining sources of exposure may still impose meaningful human-capital costs when they are spatially concentrated near children. Second, the results suggest that the benefits of eliminating leaded aviation gasoline may extend beyond health improvements to include gains in educational achievement and educational attainment. Because children attending schools nearest to high-activity airports bear the highest estimated costs, policies targeting the transition to unleaded aviation fuel may generate especially large benefits in communities located near these airports.

This study also has several limitations that should be considered when interpreting the findings. We do not observe individual blood-lead levels, so our estimates should be interpreted as reduced-form effects of increased PEA activity rather than as structural dose-response estimates. Our earnings data capture early-career outcomes only through ages 22 and 23 and only for employment observed in Texas, limiting our ability to assess longer-run labor market consequences. Future work linking aviation lead exposure to direct measures of blood lead, health outcomes, and adult earnings over a longer horizon would help clarify the full welfare costs of this remaining source of lead pollution. Nevertheless, the evidence in this paper indicates that lead emissions from PEA have measurable consequences for children's educational trajectories, reinforcing the policy relevance of eliminating remaining sources of airborne lead.

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Tables and Figures

Table 1: Summary Statistics of Airports

Variable	(1) Airports with PEA Change ≤ 25	(2) Airports with PEA Change $> 2{,}000$	(3) Difference	(4) t-statistic
Average PEA Activity (2000-2010)	227.58	7,422.98	-7,195.40***	-18.45
Total PEA Activity (2008)	237.38	10,367.50	-10,130.12***	-26.22
Total PEA Activity (2007)	246.25	6,210.64	-5,964.39***	-17.93
PEA Activity Difference (2008-2007)	-8.88	4,156.86	-4,165.73***	-31.25
Lead at nearest monitor ($\leq$25 mi): μg/m^3	0.71	5.99	-5.27*	-2.24
$PM_{2.5}$ at nearest monitor ($\leq$25 mi): μg/m^3	115.68	117.57	-1.89	-0.26
Observations	176	154		

Notes: This table reports sample means for airports with a change in PEA activity of 25 or fewer and for airports with a change in PEA activity greater than 2,000 between 2007 and 2008. It also reports differences in means between the two groups and the corresponding t-statistics from two-sample t-tests. The sample includes annual observations for these airports from 2000 through 2010. PEA refers to piston-engine aircraft. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 2: Summary Statistics

	PEA Changed >2000 × Within 1 Mile		PEA Changed >2000 × 1–3 Miles		PEA Changed ≤25 × Within 1 Mile		PEA Changed ≤25 × 1–3 Miles	
	Mean	Count	Mean	Count	Mean	Count	Mean	Count
Student and School Level Characteristics								
Total Funding (millions)	1970.125	1779	1182.916	21848	416.225	2144	659.693	14878
Female	0.478	1848	0.481	22289	0.495	2178	0.491	14948
White	0.210	1848	0.304	22289	0.364	2178	0.258	14948
Hispanic	0.653	1848	0.548	22289	0.390	2178	0.608	14948
Black	0.116	1848	0.113	22289	0.209	2178	0.118	14948
Bilingual Program	0.405	1848	0.227	22289	0.187	2178	0.205	14948
Eligible for Free Meal	0.562	1823	0.425	22054	0.546	2146	0.488	14824
Outcome Variables								
Third Grade Reading Scores	-0.046	1726	0.020	21133	-0.196	2036	-0.096	14170
Not Take Third Grade Reading Test	0.066	1848	0.052	22289	0.065	2178	0.052	14948
Third Grade Math Scores	-0.042	1623	-0.004	20002	-0.080	1793	-0.103	13210
Not Take Third Grade Math Test	0.122	1848	0.103	22289	0.177	2178	0.116	14948
Ever HS Graduation	0.722	1848	0.762	22289	0.649	2178	0.689	14948
On-Time HS Graduation (9 Years Post Grade 3)	0.665	1848	0.707	22289	0.596	2178	0.624	14948
Any College Enrollment	0.456	1848	0.541	22289	0.396	2178	0.459	14948
On-Time College Enrollment (10 Years Post Grade 3)	0.404	1848	0.478	22289	0.331	2178	0.399	14948
Public University Enrollment	0.212	1848	0.258	22289	0.132	2178	0.165	14948
On-Time Public University Enrollment	0.152	1848	0.184	22289	0.082	2178	0.118	14948
Community College Enrollment	0.366	1848	0.445	22289	0.339	2178	0.389	14948
On-Time Community College Enrollment	0.301	1848	0.366	22289	0.271	2178	0.322	14948
Associate Degree	0.090	1848	0.088	22289	0.077	2178	0.092	14948
Bachelor's Degree or Higher	0.174	1848	0.201	22289	0.099	2178	0.115	14948
Annual Earnings at Age 22 (Missing = 0)	13972.842	1848	14230.275	22289	12059.743	2178	13040.469	14948
Have Positive Earnings at Age 22	0.596	1848	0.619	22289	0.560	2178	0.620	14948
Annual Earnings at Age 23 (Missing = 0)	16455.131	1848	17152.311	22289	13720.202	2178	15014.110	14948
Have Positive Earnings at Age 23	0.588	1848	0.615	22289	0.566	2178	0.614	14948
Total Crime (9 Years Post Grade 3)	0.231	1848	0.246	22289	0.224	2178	0.291	14948
Total Violent Incidents (9 Years Post Grade 3)	0.356	1848	0.425	22289	0.466	2178	0.575	14948
Total Disciplinary Incidents (9 Years Post Grade 3)	4.273	1848	4.756	22289	7.038	2178	6.467	14948
Have Any Crime (9 Years Post Grade 3)	0.087	1848	0.080	22289	0.077	2178	0.095	14948
Have Any Violent Incidents (9 Years Post Grade 3)	0.136	1848	0.146	22289	0.177	2178	0.191	14948
Have Any Disciplinary Incidents (9 Years Post Grade 3)	0.543	1848	0.507	22289	0.614	2178	0.609	14948
Attendance Rate in Grade 3 (%)	96.835	1848	96.693	22289	95.768	2178	96.425	14948

Notes: The table reports means and observation counts for the four groups defined by treatment status (PEA change >2,000 vs. ≤25 in 2008 relative to 2007) and distance to airport (within 1 mile vs. 1–3 miles). The sample includes third-grade students attending Texas public schools within 3 miles of airports with PEA operations from 2005 to 2009.

Table 3: Balance Checks

	(1) Funding	(2) Free Meal	(3) Female	(4) White	(5) Hispanic	(6) Black	(7) Bilingual
DDD	88.471	-0.026	-0.022	-0.019	0.035	-0.037	0.003
	(239.434)	(0.039)	(0.021)	(0.036)	(0.032)	(0.024)	(0.030)
Control Mean	677.79	0.47	0.49	0.25	0.62	0.12	0.21
Observations	70263	71261	71261	71261	71261	71261	71261

Notes: This table tests whether the increase in PEA traffic is associated with changes in school resources or student composition using the triple-differences model from equation 1. "DDD" indicates PEA Increased >2000 × Post 2007 × Within 1 Mile. The dependent variables are total school funding (in millions of dollars), the share of students eligible for free meals, and shares of female, White, Hispanic, Black, and bilingual-program students. All specifications include school and year fixed effects. Standard errors are clustered at the school level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Effects on Educational Outcomes

	(1) Reading	(2) Math	(3) HS Graduation	(4) Any College	(5) Public University	(6) Community College	(7) Associate Degree	(8) Bachelor+ Degree
DDD	-0.168**	-0.065	-0.045**	-0.031	-0.039**	0.002	-0.029	-0.010
	(0.080)	(0.097)	(0.019)	(0.020)	(0.017)	(0.022)	(0.021)	(0.013)
Control Mean	-0.119	-0.122	0.698	0.455	0.157	0.382	0.107	0.089
Observations	68227	65841	71261	71261	71261	71261	71261	71261

Notes: This table reports estimates from the triple-differences model from equation 1. "DDD" indicates PEA Increased >2000 × Post 2007 × Within 1 Mile. The sample includes third-grade students attending Texas public schools within 3 miles of airports with PEA operations from 2005 to 2009. The control mean indicates the average outcome for students attending schools 1–3 miles away from airports with PEA changes of 25 or fewer. All specifications include school and year fixed effects. Standard errors are clustered at the school level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effects on On-Time Educational Outcomes

	(1) Not Take Reading Test	(2) Not Take Math Test	(3) On-Time HS Graduation	(4) On-Time Any College	(5) On-Time Public University	(6) On-Time Community College
DDD	-0.004	0.035	-0.042**	-0.046**	-0.041***	-0.015
	(0.017)	(0.024)	(0.019)	(0.019)	(0.013)	(0.023)
Control Mean	0.046	0.086	0.631	0.403	0.114	0.323
Observations	71261	71261	71261	71261	71261	71261

Notes: This table reports estimates from the triple-differences model from equation 1 for on-time completion outcomes. "DDD" indicates PEA Increased >2000 × Post 2007 × Within 1 Mile. "Not Take Reading/Math" indicates the student did not take the third-grade standardized test. On-time high school graduation is defined as graduating within 9 years of third grade; on-time college/university/community-college enrollment indicates enrolling in a college or university within 10 years of third grade. All other sample and specification details follow Table 4. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effects on Behavioral Outcomes

	(1) Total Crime	(2) Total Violence	(3) Total Disciplinary	(4) Any Crime	(5) Any Violence	(6) Any Disciplinary	(7) Attendance (%)
DDD	0.001	-0.011	0.084	-0.010	-0.011	-0.062*	-0.306
	(0.042)	(0.059)	(0.481)	(0.014)	(0.019)	(0.034)	(0.229)
Control Mean	0.292	0.575	6.172	0.096	0.190	0.597	96.421
Observations	71261	71261	71261	71261	71261	71261	71261

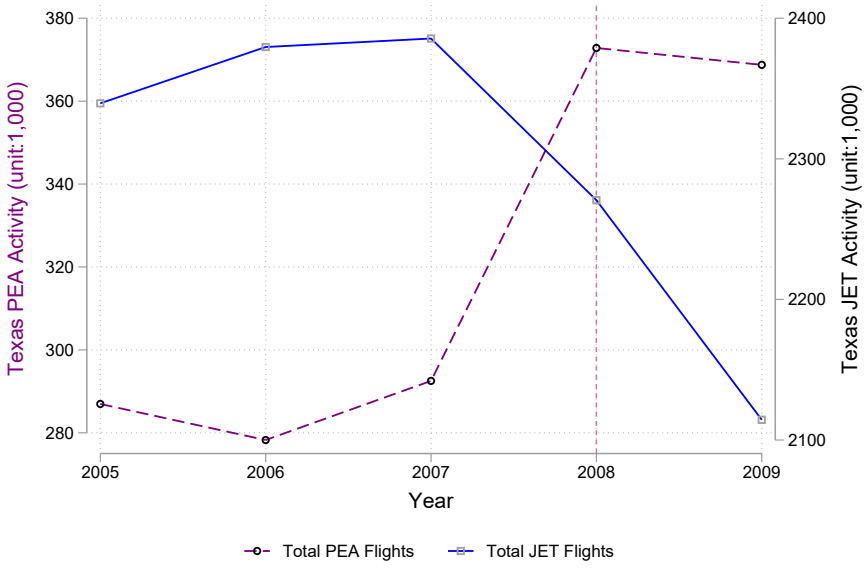
Notes: This table reports estimates from the triple-differences model from equation 1 for behavioral outcomes. "DDD" indicates PEA Increased >2000 × Post 2007 × Within 1 Mile. Total crime, violence, and disciplinary incidents are cumulated over the 9 years following third grade. "Any" indicators equal one if the student had at least one such incident. Attendance is measured as the percentage of days attended in third grade. All other sample and specification details follow Table 4. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Effects on Earnings Outcomes

	(1)	(2)	(3)	(4)
	Earnings at Age 22		**Earnings at Age 23**	
	Annual Earnings	Have Any Earnings	Annual Earnings	Have Any Earnings
DDD	-495.20	-0.05**	-140.32	-0.03
	(816.81)	(0.02)	(956.50)	(0.02)
Control Mean	13932.66	0.63	15631.13	0.61
Observations	71261	71261	71261	71261

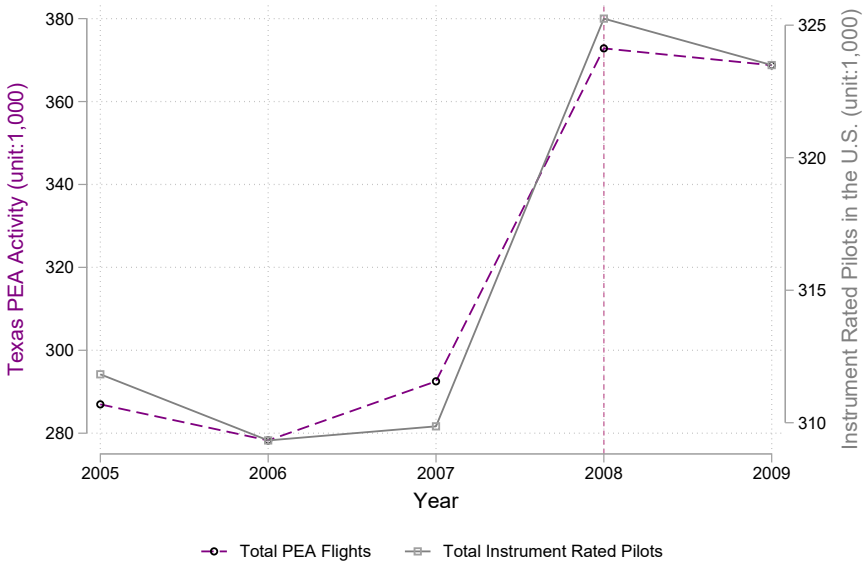
Notes: This table reports estimates from the triple-differences model from equation 1 for early-career earnings outcomes. "DDD" indicates PEA Increased >2000 × Post 2007 × Within 1 Mile. Annual earnings set missing values to zero; "Have Any Earnings" is an indicator for having positive annual earnings. Earnings are measured at ages 22 and 23. All other sample and specification details follow Table 4. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: PEA and JET Operations from 2005 to 2009 in Texas



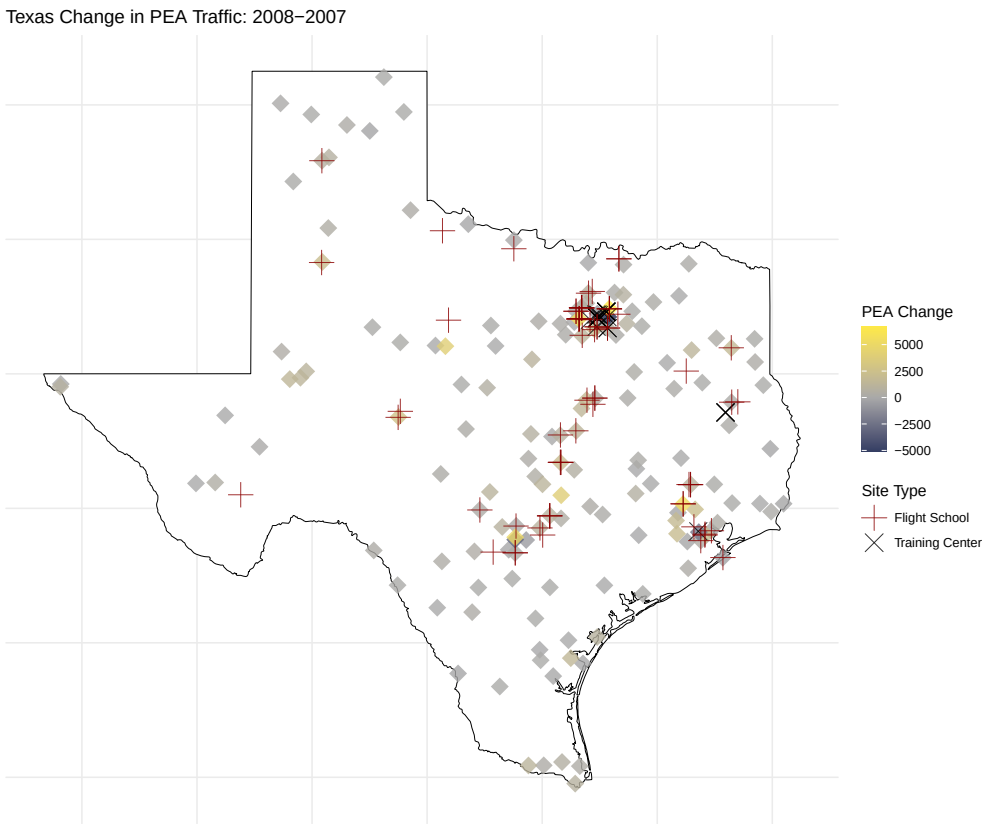
Notes: This figure shows total annual PEA and JET activity in Texas — combined flight departures and arrivals — from 2005 to 2009.

Figure 2: PEA Activity in Texas and Instrument-Rated Pilots in the United States



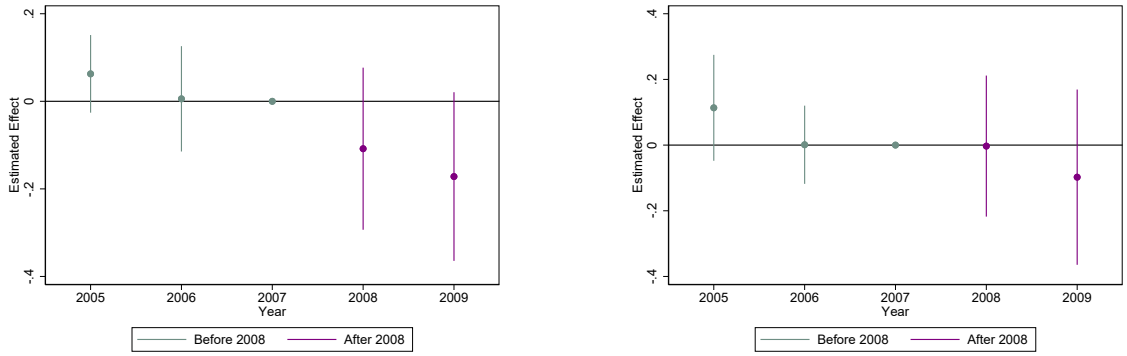
Notes: This figure shows annual PEA activity in Texas, as the sum of flight departures and arrivals, and the number of instrument-rated pilots in the United States from 2005 to 2009. The PEA activity data come from the FAA and we obtain the annual pilot counts from U.S. Civil Airmen Statistics 2013.

Figure 3: Flight Schools, Training Centers, and PEA Operations in Texas



Notes: This figure shows the change in PEA activity in 2008 compared to 2007, the site of pilot schools, and training centers in Texas in 2025.

Figure 4: Effects of Higher PEA Traffic on Test Scores

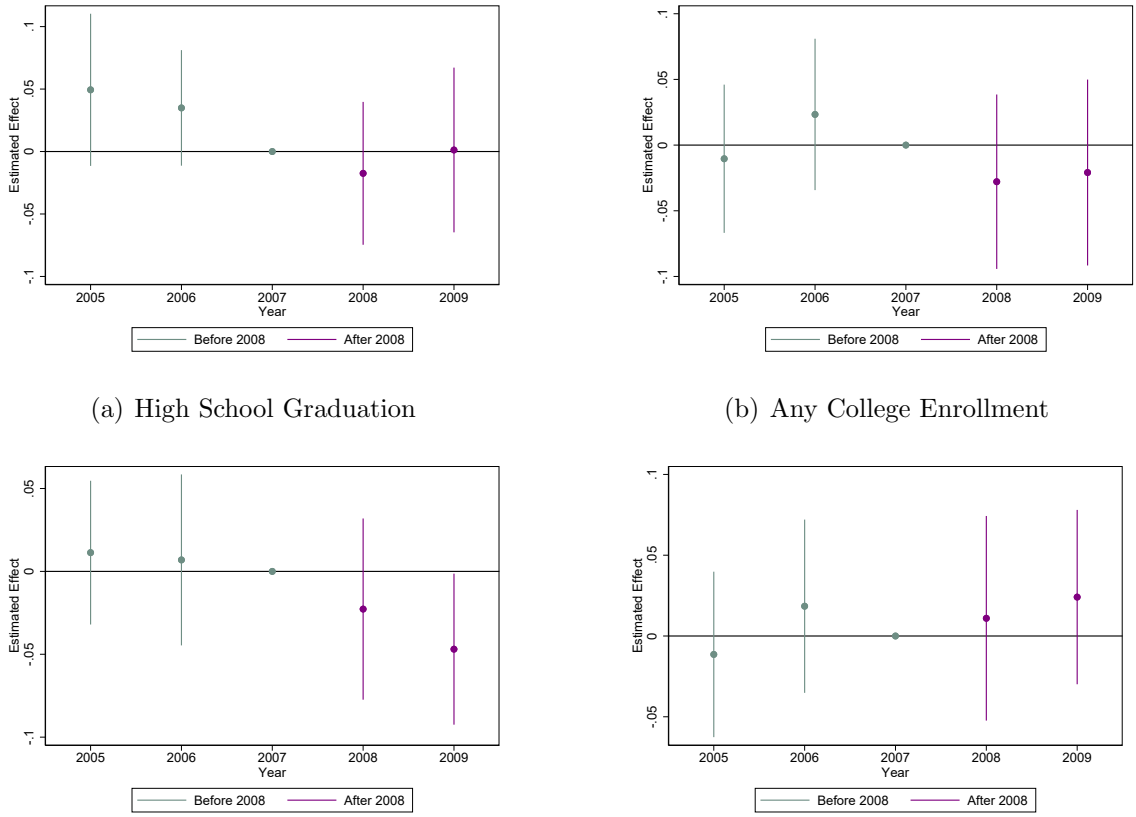


(a) Reading Scores

(b) Math Scores

Notes: This figure plots event-study estimates from the triple-differences from equation 1 for third-grade standardized test scores. Each coefficient captures the differential change in outcomes for students in schools within 1 mile of airports with PEA change > 2000 relative to schools 1–3 miles away, compared with the same differential at airports with PEA change ≤ 25, for each year relative to the 2007 baseline. The sample includes third-grade students attending Texas public schools within 3 miles of airports with PEA operations from 2005 to 2009. Whiskers indicate 95% confidence intervals. Standard errors are clustered at the school level.

Figure 5: Effects of Higher PEA Traffic on Long-Term Educational Outcomes



(a) High School Graduation

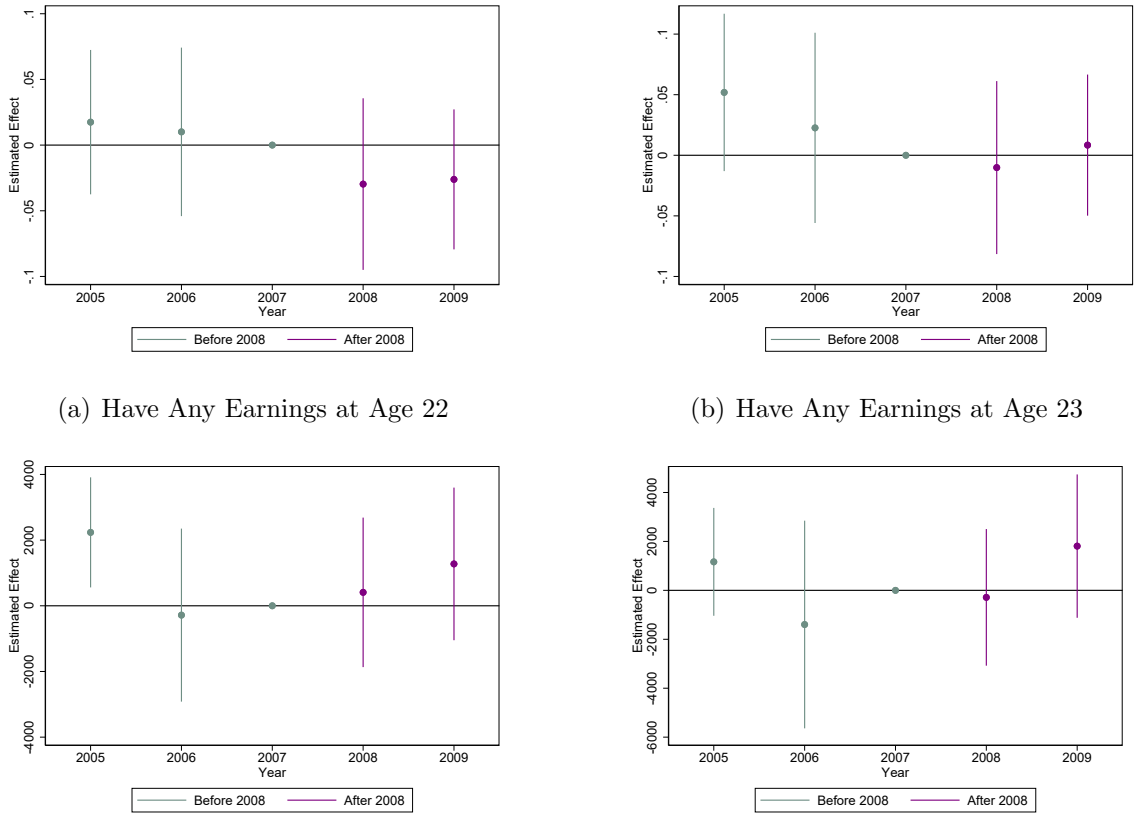
(b) Any College Enrollment

(c) Public University Enrollment

(d) Community College Enrollment

Notes: This figure plots event-study estimates from the triple-differences model from equation 1 for long-term educational attainment. Each coefficient captures the differential change in outcomes for students in schools within 1 mile of airports with PEA change > 2000 relative to schools 1–3 miles away, compared with the same differential at airports with PEA change ≤ 25, for each year relative to the 2007 baseline. High school graduation is an ever-graduation indicator; college enrollment captures any enrollment within the data window up to 2021. The sample includes third-grade students attending Texas public schools within 3 miles of airports from 2005 to 2009. Whiskers indicate 95% confidence intervals. Standard errors are clustered at the school level.

Figure 6: Effects of Higher PEA Traffic on Early Earnings Outcomes



(a) Have Any Earnings at Age 22

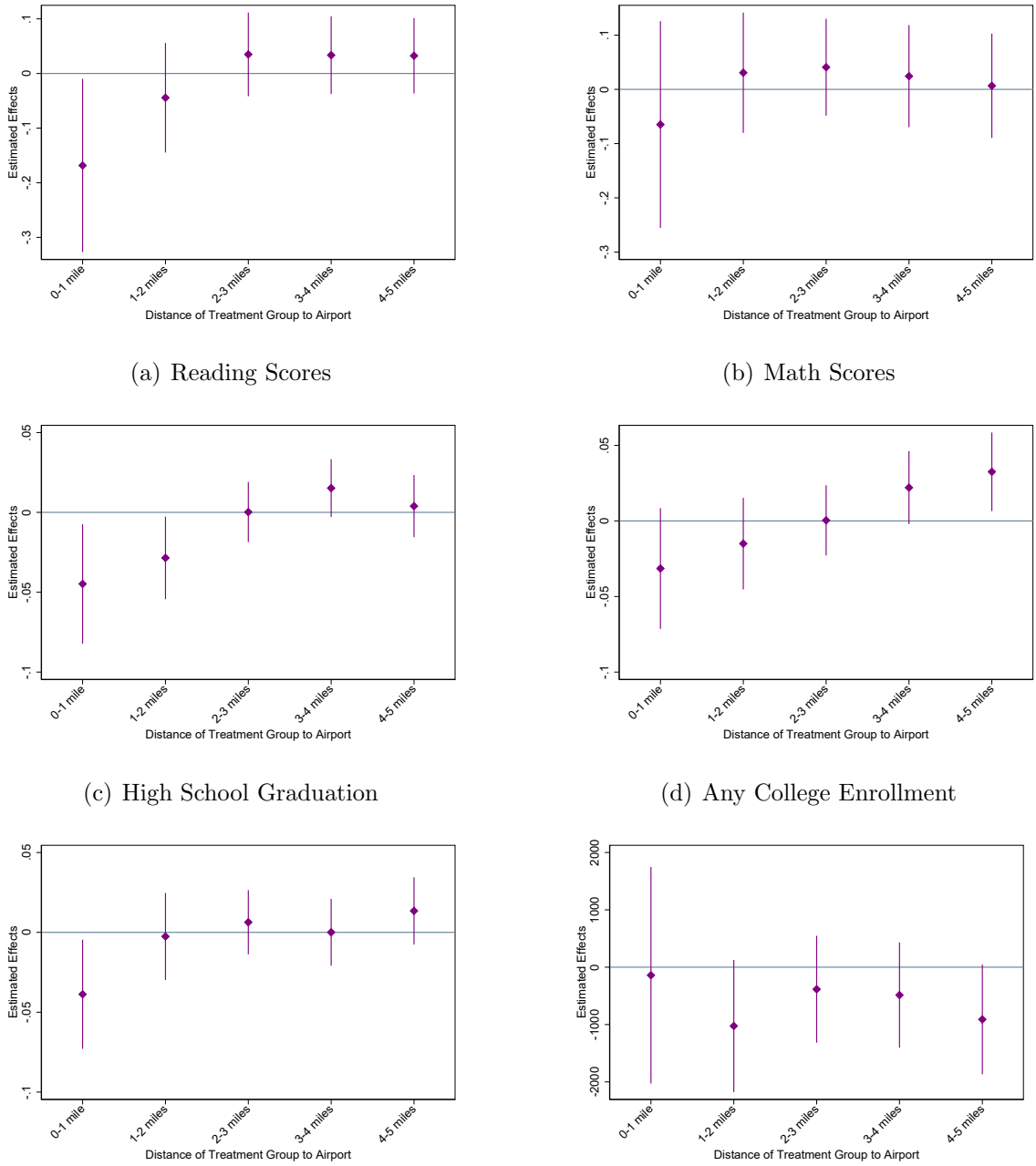
(b) Have Any Earnings at Age 23

(c) Annual Earnings at Age 22

(d) Annual Earnings at Age 23

Notes: This figure plots event-study estimates from the triple-differences model from equation 1 for early-career earnings. Each coefficient captures the differential change in outcomes for students in schools within 1 mile of airports with PEA change > 2000 relative to schools 1–3 miles away, compared with the same differential at airports with PEA change ≤ 25, for each year relative to the 2007 baseline. Annual earnings set missing values to zero. The sample includes third-grade students attending Texas public schools within 3 miles of airports from 2005 to 2009. Whiskers indicate 95% confidence intervals. Standard errors are clustered at the school level.

Figure 7: Effects on Students' Outcomes by Distance to Airport



(a) Reading Scores

(b) Math Scores

(c) High School Graduation

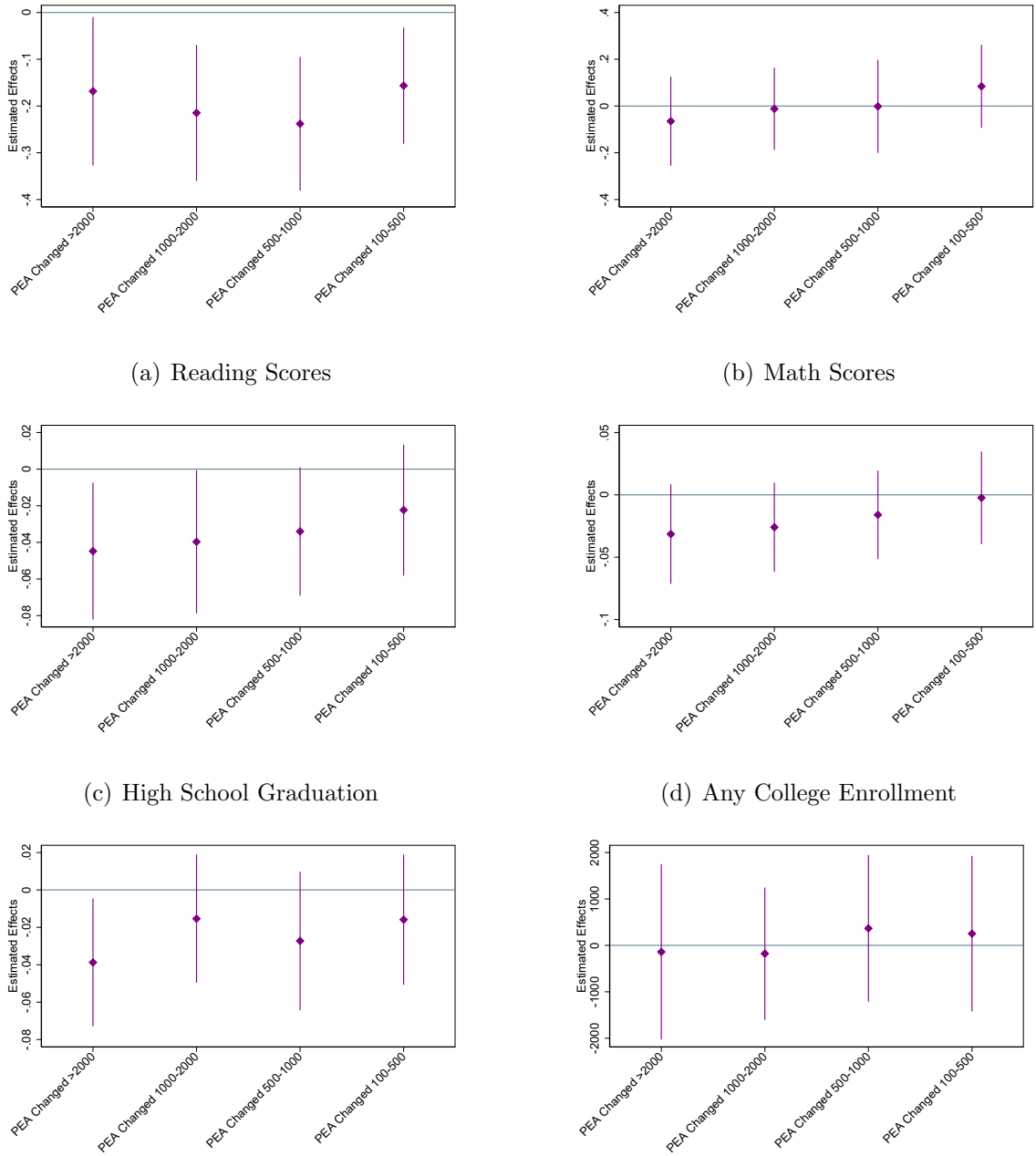
(d) Any College Enrollment

(e) Public University Enrollment

(f) Annual Earnings at Age 23

Notes: This figure reports triple-differences estimates from separate regressions that vary the distance band used to define the treatment group. Each coefficient compares schools in the indicated one-mile distance band to schools located two miles farther from the airport. For example, the 0–1 mile estimate uses schools 0–1 mile from the airport as the treatment group and schools 1–3 miles away as the comparison group. The sample includes third-grade students attending Texas public schools near airports with PEA operations from 2005 to 2009. Whiskers indicate 95 percent confidence intervals. Standard errors are clustered at the school level.

Figure 8: Effects on Students' Outcomes by PEA Traffic Intensity



(a) Reading Scores

(b) Math Scores

(c) High School Graduation

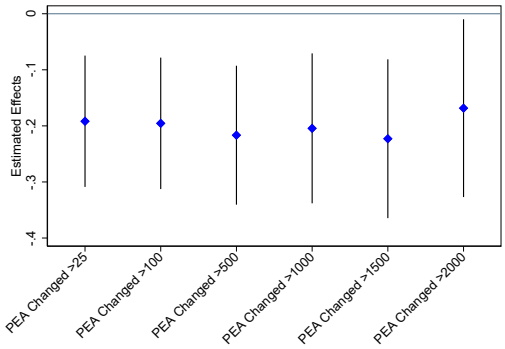
(d) Any College Enrollment

(e) Public University Enrollment

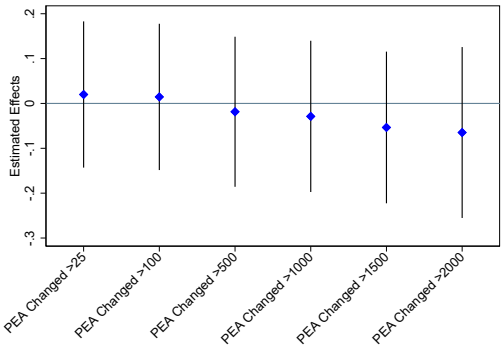
(f) Annual Earnings at Age 23

Notes: This figure presents triple-differences estimates using alternative measures of PEA traffic intensity for the treatment group. Each point estimates the effect for a different intensity bin, based on the triple-differences specification. The sample includes 3rd-grade students from 2005 to 2009. Whiskers indicate 95% confidence intervals. Standard errors are clustered at the school level.

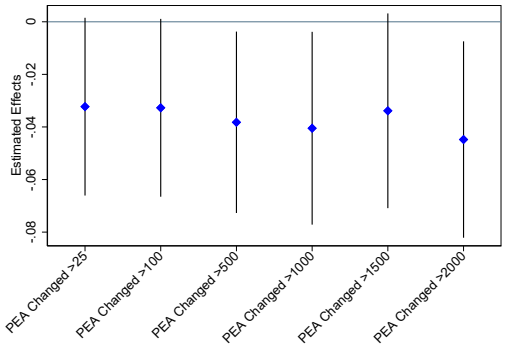
Figure 9: Effects on Students' Outcomes by PEA Traffic Intensity Cutoff



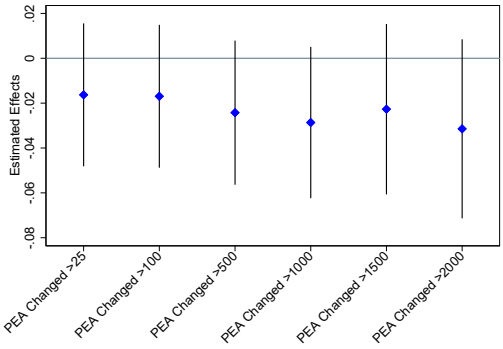
(a) Reading Scores



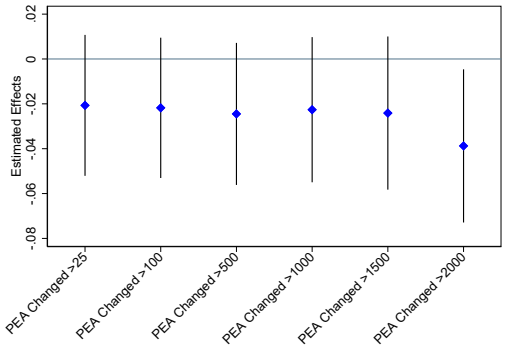
(b) Math Scores



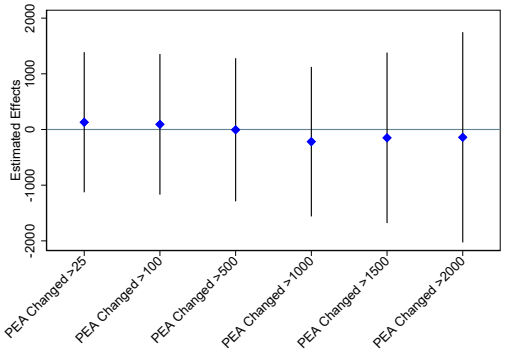
(c) High School Graduation



(d) Any College Enrollment



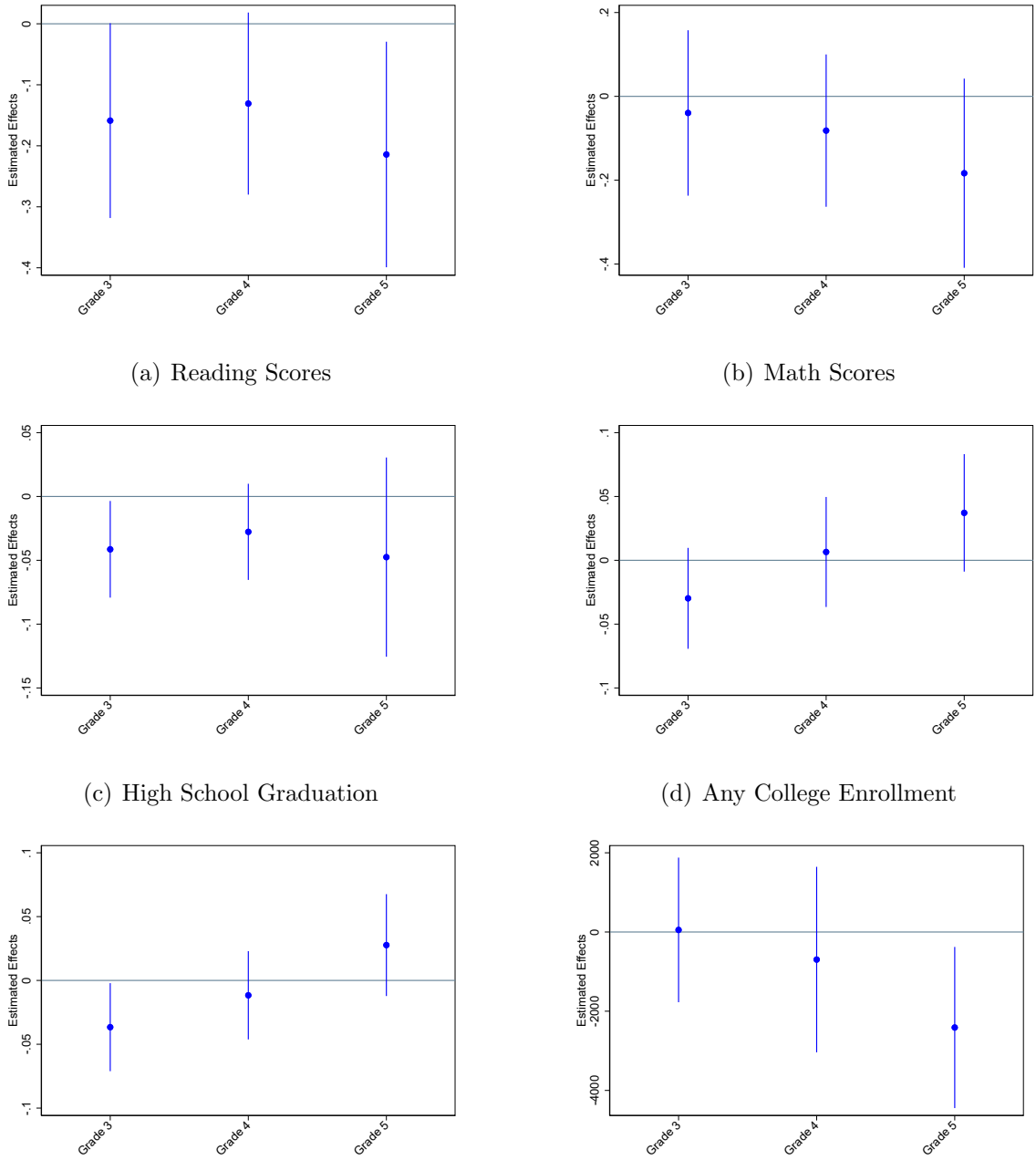
(e) Public University Enrollment



(f) Annual Earnings at Age 23

Notes: This figure presents triple-differences estimates as the treatment cutoff for PEA traffic intensity is varied. Each coefficient is estimated from a separate regression using the triple-differences specification, holding the control-group cutoff fixed at changes of 25 or fewer PEA operations. The sample includes 3rd-grade students from 2005 to 2009. Whiskers indicate 95% confidence intervals. Standard errors are clustered at the school level.

Figure 10: Effects on Students' Outcomes by Grade at Exposure



(a) Reading Scores

(b) Math Scores

(c) High School Graduation

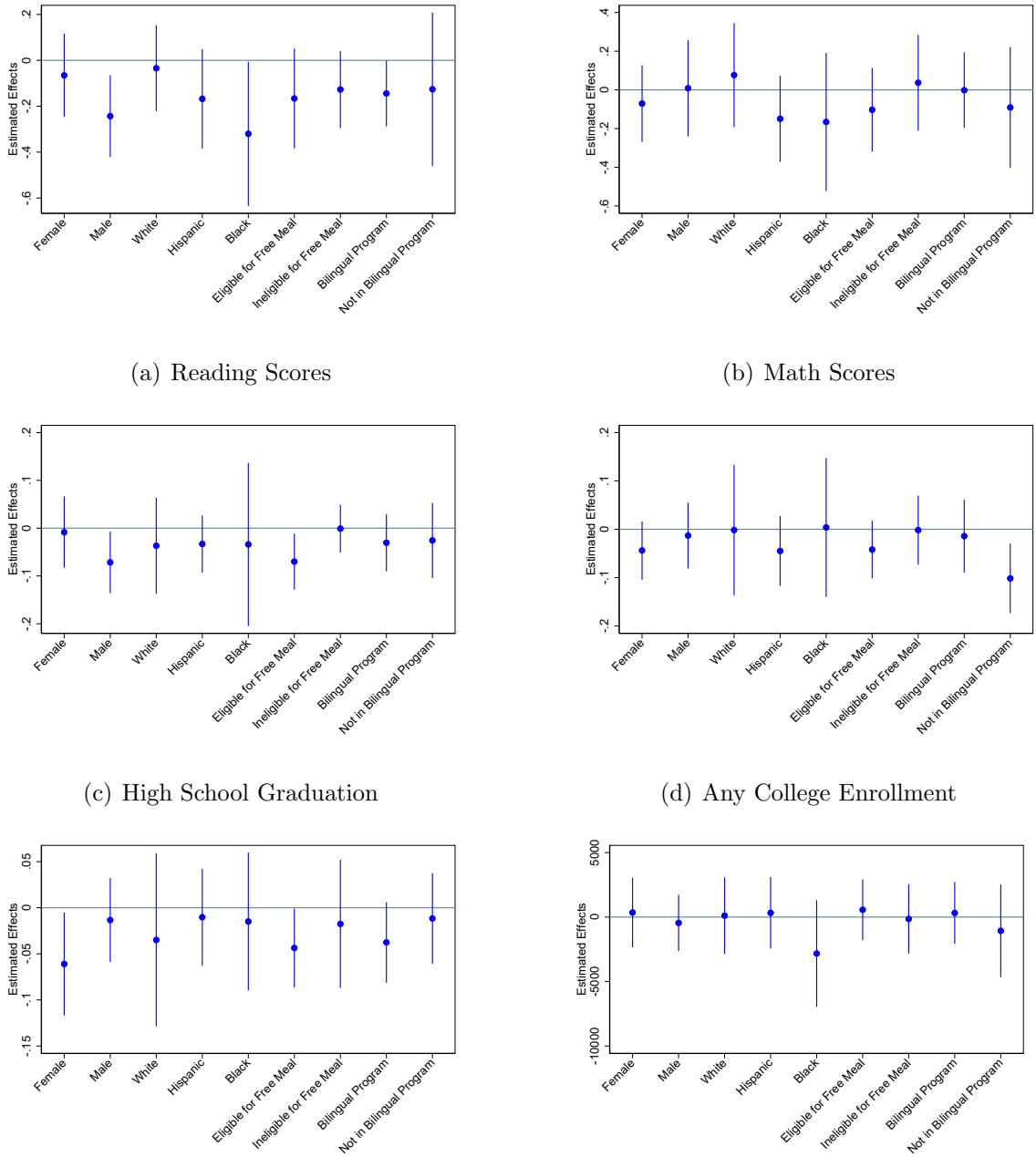
(d) Any College Enrollment

(e) Public University Enrollment

(f) Annual Earnings at Age 23

Notes: This figure presents the triple-differences estimates by the grade in which students were exposed to the PEA spike around 2008, using the triple-differences specification estimated separately for each grade. The sample includes 3rd- through 5th-grade students from 2005 to 2009. Whiskers indicate 95% confidence intervals. Standard errors are clustered at the school level.

Figure 11: Effects on Students' Outcomes by Subgroups



(a) Reading Scores

(b) Math Scores

(c) High School Graduation

(d) Any College Enrollment

(e) Public University Enrollment

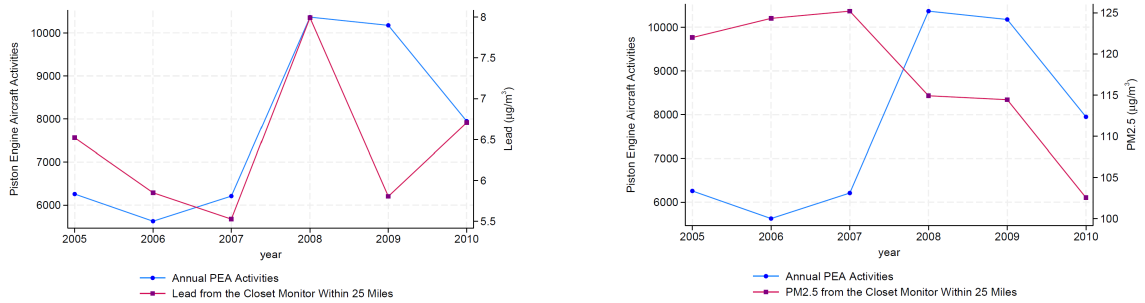
(f) Annual Earnings at Age 23

Notes: This figure presents triple-differences estimates by student subgroup (e.g., by gender, race/ethnicity, free-meal eligibility, or participation in bilingual program). The sample includes 3rd-grade students from 2005 to 2009. Whiskers indicate 95% confidence intervals. Standard errors are clustered at the school level.

Online Appendix for "Low-Level Lead Exposure and Children's Human Capital: Evidence from Piston-Engine Aircraft" by Thao Duong and Jiee Zhong

Appendix A: Additional Results

Figure A1: PEA Activity, Lead Concentration, and $PM_{2.5}$

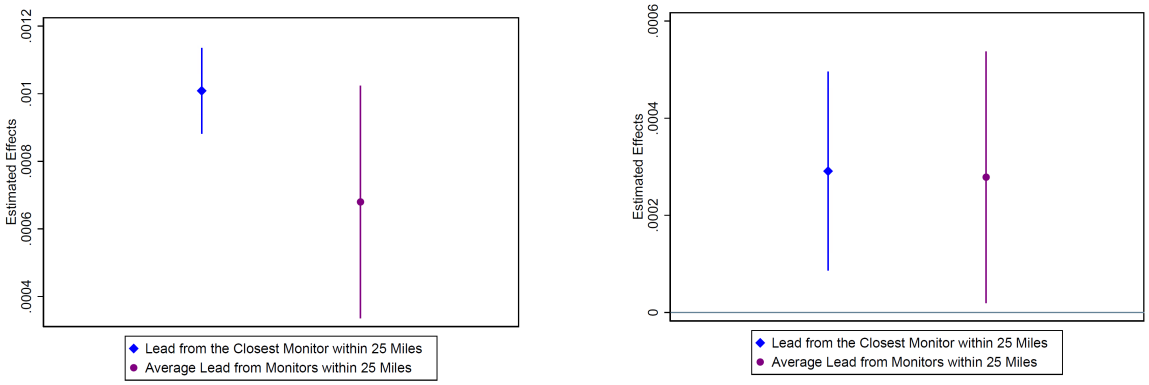


(a) PEA and Lead

(b) PEA and $PM_{2.5}$

Notes: This figure plots trends of PEA activity, lead concentration, and $PM_{2.5}$ for airports with PEA change larger than 2000 from 2008 to 2007 conditional on having a monitor within 25 miles.

Figure A2: Effects of PEA Traffic on Lead Concentration



(a) Airports from Treatment Group

(b) Airports With Monitor within 25 Miles

Notes: Figure (a) plots predicted lead concentrations for airports whose PEA activity changed by more than 2,000 between 2007 and 2008, restricted to airports with a lead monitor within 25 miles. Predictions come from an OLS regression of lead concentration on PEA activity, estimated over 2000–2010. Figure (b) shows the predicted effect in all airports with a monitor within 25 miles.

Table A1: Robustness Checks

	(1) Reading	(2) Math	(3) HS Graduation	(4) Any College	(5) Public University	(6) Community College	(7) Annual Earnings Age 22	(8) Annual Earnings Age 23
DDD	-0.159*	-0.040	-0.041**	-0.030	-0.037**	0.004	-333.585	52.491
	(0.081)	(0.100)	(0.019)	(0.020)	(0.017)	(0.021)	(803.457)	(925.016)
Control Mean	-0.12	-0.12	0.70	0.46	0.16	0.38	13932.66	15631.13
Observations	68227	65841	71261	71261	71261	71261	71261	71261

Notes: This table replicates the main triple-differences estimates (Tables 4 and 7) without including any control variables. "DDD" indicates PEA Increased >2000 × Post 2007 × Within 1 Mile. The specification retains school and year fixed effects. Standard errors are clustered at the school level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.