Toxic Recycling: The Cost of Used Lead-Acid Battery Processing in Mexico*

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PRELIMINARY - DO NOT CITE

Abstract

There is no known safe level of lead pollution exposure. Many countries have taken steps in the last half century to remove lead from their environments, but, at times, these policies can cause pollution sources to shift to countries with weaker regulatory environments. Previous studies have theorized about and empirically documented this 'pollution haven' phenomenon, but few have examined the costs borne by recipient communities. In the setting we study, a 2009 tightening of environmental standards in the United States caused used lead-acid battery recycling, an industry that emits large amounts of lead pollution, to shift to Mexico. We estimate the effects of this increased industrial activity and associated pollution on student learning in recipient communities in Mexico. We use data from a nationwide test in Spanish and math, conducted from 2006 to 2013. We compare test scores before and after the 2009 U.S. policy change among students attending schools near and downwind of Mexican recycling facilities and those studying farther away. We estimate effects on test scores of negative 0.05-0.09 standard deviations, with effects being slightly stronger for math than Spanish. Comparing dynamic effects across grades, we find suggestive evidence that effects are stronger for students who were younger in 2009. We also compare effects across communities, showing that the costs to education are heavily concentrated in communities that were already worse off before the 2009 change in lead-acid battery recycling activity. The results of our study underline the importance of considering unintended consequences and cross-border spillovers when regulating toxic pollutants. The heterogeneity of effects across communities highlights the need for more research on the costs of lead pollution exposure in low- and middle-income countries, where the vast majority of exposure occurs today.

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1 Introduction

There is no safe level of lead pollution exposure; even small exposures can have damaging health and developmental effects (Centers for Disease Control and Prevention, 2013).[1] Children are especially vulnerable due to greater lead absorption and developmental disruption (Rees & Fuller, 2020). Empirical evidence from rich countries highlights the exposure consequences for children, including reduced IQ, diminished educational achievement, and increased antisocial behaviors (Ferrie, Rolf, & Troesken, 2012; Reyes, 2015; Aizer & Currie, 2019; Gronqvist, Nilsson, & Robling, 2020).[2] Regulatory measures like removing lead from gasoline, banning lead in paint, and setting ambient pollution standards, have been successful at reducing exposure, especially in rich countries.[3] However, these same measures can unintentionally shift lead pollution to lower-income countries with weaker environmental regulations. Significant efforts have been put towards documenting *when* this shifting of pollution may take place, e.g. Copeland, Shapiro, and Taylor (2022), but there has been little focus on the *effects* of this relocation on recipient communities.

We study the effects of one such case — the relocation of a lead-intensive and polluting industry, used lead-acid battery (ULAB) recycling, from the U.S. to Mexico. We estimate the costs of this relocation of pollution, specifically those related to educational achievement, on recipient communities. In 2009, the U.S. Environmental Protection Agency tightened regulatory standards for lead, successfully reducing airborne lead concentrations around battery recycling plants in the U.S. and prompting ULAB recycling activities to shift to Mexico (Tanaka, Teshima, & Verhoogen, 2022). We identify children living near

[1] Lead is a neurotoxin; it affects cardiovascular and renal health; and, in some cases, exposure can be lethal (Ara & Usmani, 2015).

[2] Other relevant papers include Aizer, Currie, Simon, and Vivier (2018); Sorensen, Fox, Jun, and Martin (2019); Gazze, Persico, and Spirovska (in press); Zheng (2021); Hollingsworth, Huang, Rudik, and Sanders (2022).

[3] For example, the U.S. reduced airborne lead pollution by about 90 percent between 1980 and 2016 (U.S. Environmental Protection Agency, 2014) and continues to make progress on reducing lead exposure.

Mexican recycling plants between 2006 and 2013 and estimate the effect of this influx of lead-intensive industrial activity and its associated pollution on their learning.

Previous studies have estimated the causal effects of lead exposure on learning, IQ, and other educational outcomes in rich countries like the United States, e.g. Sorensen et al. (2019), and Sweden, e.g. Gronqvist et al. (2020). These findings may underestimate the costs of pollution exposure in low- and middle-income countries if families in lower-income settings are less able to counteract the effects of lead exposure via, for example, increasing educational inputs, receiving medical treatments, or engaging in pollution averting behaviors. Heterogeneity analyses in rich country settings suggest that the effects of pollution can be worse in settings with higher poverty (Hollingsworth et al., 2022).

To identify causal effects in Mexico, we use a difference-in-difference (DID) design, comparing children attending schools close to and farther away from battery recycling sites, before and after the 2009 U.S. policy change that shifted battery recycling activities to Mexico.[4] From our data sources we know the locations of 26 authorized battery recycling facilities and the locations of all schools in Mexico. We measure academic achievement using student-level panel data from a nationwide standardized exam that tested math and Spanish proficiency between 2006 and 2013. We observe the universe of students tested in this exam, which, at its peak, administered tests to almost 14 million students each year.

We find that exposure to lead-battery recycling reduces academic achievement. The post-2009 increase in recycling activity negatively affects learning for students attending schools within 2-miles of a battery recycling plant. Math test scores at these schools decreased between 0.05-0.09 standard deviations (σ) after 2009, relative to students in schools farther away but in the same state. For Spanish, we also estimate negative, though slightly smaller, effects (0.05-0.07σ). Event study results show that the pre-2009 trends in test scores do not differ by distance to a recycling plant (supporting the identification

[4]There is no lead pollution monitoring network across Mexico. Thus, we cannot study the direct impact of the policy change in 2009 on lead exposure and lead levels. Instead, we focus on the reduced form effect of the policy shift in 2009 on outcomes for residents near the recycling plants in Mexico.

assumption of the difference-in-difference design). Further, the event studies suggest the effects of the increase in lead pollution worsen over time.

The results are robust to alternative specifications that guard against other determinants of learning that may also vary with distance to the recycling plant. For example, factors such as growth in labor demand, which could have accompanied the post-2009 increase in recycling activity, could affect wages and local economic activity near the plants. This could, in turn, affect household incomes and children's education. We can test for this by defining exposed schools based not just on distance but also on prevailing wind direction. The addition of wind direction helps us more precisely identify lead exposed students as environmental studies of lead pollution around battery recycling plants and other lead smelters show that pollution levels correlate with prevailing winds (Ettler, 2016). Comparing test scores at schools nearby *and* downwind from recycling facilities to those upwind and/or farther away we find similar and slightly larger effect sizes (-0.09-0.11σ for math, -0.09-0.10σ for Spanish).

Another concern is selective sorting, based on both the post-2009 increase in pollution and the potential economic changes accompanying the increase in battery recycling. The increase in battery recycling could induce migration if families either move away from the area due to increased pollution or move towards the area because of new economic opportunities. If movers are not randomly drawn from the ability distribution, this could bias our results. We can directly observe moving in our student-level panel: we know the school each student attended in a given year and the location of that school. To test whether selective migration is driving our results we assign the post-2009 exposure variable, indicating whether a student is studying near a battery recycling facility, based on their 2008 location. In this way, this inference method is similar to an "intent-to-treat" design. Our results are robust to these specifications, though slightly smaller (-0.06-0.11σ for math, -0.03-0.07σ for Spanish).

Finally, we consider whether and how lead exposure affects different individuals and communities. Our finding that effects of exposure worsen over time could be driven by increasing pollution levels or differences in effects based on student's age (at first exposure). By estimating dynamic effects separately for each grade, we can isolate age effects from increasing or chronic pollution effects. Consistent with the medical literature (Lidsky & Schneider, 2003), effects appear to be stronger for students first exposed at younger ages (i.e., those in kindergarten or younger as of 2009, relative to those who were older).

We can also test for heterogeneity in effects across communities. A key strength of our data and setting is that we observe the change in lead-emitting industrial activity across many locations, as compared to other studies that focus on one polluted site (Rau, Urzúa, & Reyes, 2015). This allows us to explore how effects vary across different types of communities. We use census data to measure baseline socioeconomic characteristics in the communities where schools are located. We find that, across multiple measures of socioeconomic welfare, the negative effects of the post-2009 increase in battery recycling are stronger in worse-off communities. For example, we can compare effects in communities with different levels of marginalization, defined by the Mexican government as a composite measure of literacy rates, educational attainment, housing quality, infrastructure access, and incomes. In more marginalized communities, with above median values of the marginalization index, we estimate a -0.09σ effect on math scores (t-statistic of 3.70) but, in below median communities, a less significant -0.03σ effect (t-statistic of 1.75). We find qualitatively similar results comparing effects across communities with above and below median adult education levels and formal employment rates. These results suggest that lead exposure may exacerbate inequality in educational achievement.

What can be done, from a policy perspective, to address these effects? One option is to increase regulatory stringency and/or enforcement to reduce lead emissions from battery recycling facilities. In section 5, we estimate the cost of the education effects we identify here. In terms of lost lifetime earnings for exposed students, the costs fall in the range of

16 to 39 million USD annually. This estimate ignores the other health costs associated with lead pollution and likely outweighs the expected costs of lead pollution control technology.

This study offers two main contributions to the existing social science literature on the effects of lead pollution exposure. First, few papers have assessed the causal effects of lead exposure in low- to middle-income countries. A notable exception is a study by Rau et al. (2015) who use data from the city of Arica in northern Chile to study the relationship between school proximity to toxic lead waste and students' scores in a standardized test for fourth graders and a college entrance exam.[5] They find that exposure to this hazardous waste strongly and negatively affects test scores and estimate resulting lost lifetime earnings of 60,000 USD. Findings specific to contexts outside of the Global North are important, as that is where the vast majority of lead pollution exposure and associated costs occur today (Larsen & Sánchez-Triana, 2023). Effects could differ in these settings, relative to rich countries, for multiple reasons, including higher overall emissions and weaker health and educational institutions to mitigate the effects of exposure. Additionally, location-specific estimates of pollution costs are important for regulatory design. Our study allows us to observe the total effects of one lead pollution exposure channel in a middle-income country and estimate heterogeneity across community-level characteristics. Even within Mexico, effects are concentrated in more marginalized communities, suggesting underlying levels of development matter when estimating the costs of lead pollution exposure and that estimates from rich countries may underestimate costs in less developed settings.

Second, from a methodological perspective, previous studies have primarily relied on cross-sectional data from a single grade or educational data aggreagted at the grade or school level to study the effects of lead exposure on educational outcomes (Rau et al., 2015; Aizer et al., 2018; Zheng, 2021; Gronqvist et al., 2020; C. Persico, Figlio, & Roth, 2020; Jacqz, 2022; Hollingsworth et al., 2022). In contrast, our paper tracks students' academic performance over several years to estimate the impact of lead pollution

[5] Tanaka et al. (2022) study the effects of ULAB recycling activity in Mexico on maternal and infant health outcomes.

on cognitive development, as proxied by math and Spanish test scores. Hence, the longitudinal structure of our data allows us to address the issue of student sorting as a confounding factor, a common challenge in the existing literature (Rau et al., 2015).[6] We also expand on this literature by focusing on test scores for grades 3-6 and grade 9 from 2006 to 2013, providing a more robust measure of cognitive development by capturing changes in individual students' academic achievement over time.

2 Relevant Background Information

2.1 Lead-acid battery recycling

The production of lead-acid batteries accounts for over 80 percent of the total demand for lead worldwide (International Lead and Zinc Study Group, 2019), reflecting the growing market driven by the rise in vehicle ownership in low- to middle-income countries and the global demand for energy storage solutions (Rees & Fuller, 2020). At the same time, lead demand is primarily met through secondary lead, or lead that comes from recycling, instead of primary lead that is mined. Used lead acid batteries (ULABs) have one of the highest end-of-life recycling rates (Alistair, Binks, & Gediga, 2016), and almost all lead found in them can be reclaimed.[7] Still, recycling lead is dangerous and can be heavily polluting if strict protocols and advanced technology are not used to control lead emissions during recycling (Ballantyne, Hallett, Riley, Shah, & Payne, 2018). Lead from recycling can enter the environment through a number of pathways. Lead laden gases and dust can escape during handling, separation, smelting, and refining (U.S. Environmental Protection Agency, 1995). Lead can also run into the environment through water discharges or dumping of solid wastes. Moreover, where worker safety protocols are non-existent or not enforced, workers can expose themselves and their families to lead contamination by bringing lead dust home on their clothes

[6] Student sorting can occur when there is selection into schools subject to environmental toxicants from lead-recycling plants.

[7] Besides, recycling the lead in used lead-acid batteries is a cost-effective alternative to mining it, further contributing to high recycling rates.

and skin (WHO, 2017). Thus, improper management of even small-scale lead recycling operations can cause environmental contamination and severely threaten human health (Commission for Environmental Cooperation, 2013; WHO, 2017).

Pollution and toxicology researchers have long documented the contamination that is emitted from used lead acid battery recycling sites. At two sites in Indonesia, both formal and informal, surface soil concentrations of lead were found to be as much as ten times higher than background levels, with concentrations decreasing with distance (Adventini, Santoso, Lestiani, Syahfitri, & Rixson, 2017). Airborne concentrations of lead in these areas was primarily attributed to industrial activity (Santoso et al., 2011). Samples of dust around three heavy metal processing (smelting and refining) sites in Mexico found concentrations of lead to be in excess of U.S. standards with concentrations also associated with distance to the facility's emissions stack and prevailing wind direction (Benin, Sargent, Dalton, & Roda, 1999).[8] Studies have also focused on more direct exposure measures, investigating lead levels in blood and teeth of those living around these sites. At a battery recycling facility in China, the median child had a blood lead level of 8.9 micrograms per deciliter, compared to the current U.S. standard of 3.5 micrograms per deciliter (Zhang et al., 2016).[9] Elevated blood lead levels were more likely among younger children, male children, those living closer to the recycling facility, and those who had at least one parent working in the facility. A 2011 review of studies documenting lead exposure around lead acid battery manufacturing and recycling plants in developing countries found that the average child living near a facility had a blood lead level of 29 micrograms per deciliter, significantly higher than the U.S. reference value of 3.5 (Gottesfeld & Pokhrel, 2011). Tested children living around an informal battery recycling facility in Bihar, India were all found to have lead in their blood, with the mean concentration at 24 micrograms per deciliter (Ansari,

[8]The author's of this study use Superfund cleanup site goals of 200-500 parts per million (ppm) as the standard of comparison.

[9]This U.S. non-regulatory standard set by the Center for Disease Control is known as the blood lead reference value. Children with blood lead levels above this reference value are recommended to receive intervention such as reporting the result to local health authorities, conducting an exposure assessment of the child's home, and monitoring child's nutrition and development milestones (Centers for Disease Control and Prevention, 2022).

Mahdi, Malik, & Jafar, 2020). Even in more regulated settings like the U.S., battery recycling facilities are associated with elevated lead in the body. A 1977 study of children with a parent working in a battery recycling plant in Tennessee found that almost half had blood lead levels above 25 micrograms per deciliter (Baker Jr et al., 1977). Lead exposure was more recently detected around a lead smelter that processed secondary lead from used batteries in Los Angeles, California (Johnston, Franklin, Roh, Austin, & Arora, 2019). Pre- and post-natal lead exposure was detected in shed baby teeth from children who lived within two miles of the smelter during it's time of operation.[10]

In our study we focus on used lead acid battery recycling in Mexico and study the period between 2006 and 2013. The battery recycling industry is Mexico is made up of both formal and informal firms, though due to the increasingly competitive nature of sourcing used lead acid batteries, it is expected that the majority of the small, informal operations have closed (Commission for Environmental Cooperation, 2013). As of 2014, 26 known formal recycling facilities were in operation (see Figure 1) and were estimated to be producing 401,151 tons of recycled lead annually (Tanaka et al., 2022; Commission for Environmental Cooperation, 2013). In Mexico, the Secretary of the Environment and Natural Resources (*Secretaria del Medio Ambiente Recursos Naturales* or SEMARNAT) regulates airborne lead concentrations; the standard during our study period was 1.5 micrograms per cubic meter. Companies are also required to report emissions of toxic materials via the Registry of Emissions and Transfers of Contaminants (*Registro de Emisiones y Transferencia de Contaminantes* or RETC) program). Enforcement of these regulations has been noted to be incomplete and inconsistent (Gottesfeld, Chavez Arce, & Macias Raya, 2023). More than half of the registered recycling facilities in Mexico did not report emissions during our study period and air quality monitoring outside of Mexico City is almost non-existent (Commission for Environmental Cooperation, 2013). In addition, the country does not have standards around the construction and

[10]Lead concentrations in teeth is not a commonly taken measure, so more difficult than blood concentration to compare to population levels or standards. The authors of this study cite that they find higher concentrations in their sample than those documented in a similar study in Sweden.

operation of battery recycling plants, including emissions from stacks (Commission for Environmental Cooperation, 2013). These loopholes in regulation are exacerbated because technologies to reduce lead emissions from battery recycling plants are costly, and without regulation is unlikely recycling plants in Mexico will adopt them. Consequently, emissions from Mexican recycling plants are estimated to be 20 times higher than those of their US counterparts (OK International & Fronteras Comunes, 2011). Further, labor protection regulations in Mexico permit exposure levels that are three times higher than in the US (OK International & Fronteras Comunes, 2011).

To study the effects of the pollution from the 26 facilities, we rely on an increase in their operations that was caused by a 2009 U.S. regulatory change. In January 2009, the U.S. Environmental Protection Agency reduced the air quality standard for lead from 1.5 ug/m3 to 0.15 ug/m3.[11] This regulation made it more difficult and expensive to recycle used lead-acid batteries domestically, pushing U.S. recycling facilities to close or shift activities to Mexico. Tanaka et al. (2022) document this shift, showing that the U.S. regulatory change drastically increased used battery exports from the U.S. to Mexico and increased the value of the lead battery recycling industry in Mexico, relative to other, similar industrial sectors. It's estimated that, as of 2013, 30-60 percent of all used batteries processed in Mexico came from the U.S. (Commission for Environmental Cooperation, 2013).

2.2 Health effects of lead pollution exposure

Lead poses a toxic threat regardless of how it enters the body. According to the U.S. Center for Disease Control Centers for Disease Control and Prevention (2013), there is no safe blood lead level, making any exposure hazardous, especially for fetuses, infants, and children. At high levels, lead can be lethal (WHO, 2017). At low levels, it can harm human health, acting as a cumulative toxic substance that impacts various organs and systems. The nervous system is the most susceptible as the brain's prefrontal cortex is particularly vulnerable to lead exposure. Hence, lead exposure can hinder a child's brain development resulting in

[11] While signed on May 2008, it became effective on January 2009.

learning disabilities, lower educational achievement, and even antisocial behaviors later in life (Ferrie et al., 2012; Reyes, 2015; Rau et al., 2015; Billings & Schnepel, 2018; Aizer et al., 2018; Aizer & Currie, 2019; Sorensen et al., 2019; Gronqvist et al., 2020; C. Persico et al., 2020; C. Persico, 2022; Gazze et al., in press). In response, most countries have banned lead from everyday products such as gasoline, toys, and paint. Between 1970 and 2000, this led to a significant reduction in lead exposure and pollution.

2.3 The Mexican Education System

The Mexican education system is based on a federal model, regulated by the Ministry of Education (*Secreataria de Educacion Publica* or SEP), while individual states are responsible for administration and implementation. School days are shorter than in other countries; there are two sessions each day to accommodate numerous students. These are divided into morning (8:00 am to 12:30 pm) and afternoon (2:00 pm to 6:30 pm) sessions. While these two sessions take place within the same physical school, there are essentially two different operations, with different teachers, principals, etc.[12]

The system is divided into three main levels: Basic, upper secondary, and higher Education. Basic education, which includes preschool, primary, and lower secondary education, is compulsory and free for all students. Preschool lasts three years, primary lasts six years, from grades 1 to 6, and lower secondary lasts from grades 7 to 9. Upper secondary education (grades 9-12) provides students with specialized academic and vocational training. It was not compulsory during the majority of our study period but is available to all students who have completed lower secondary education. Upper secondary became compulsory in 2012 (Santiago, McGregor, Nusche, Ravela, & Toledo, 2012), but it is the parents responsibility to make sure their children complete grade 12 and enforcement is variable across states.

[12]Starting in 2007, Mexico began rolling out the Full-time Schools Program (*Programa Escuelas de Tiempo Completo* or PETC) which increased the school day from 4.5 to 6-8 hours (Cabrera-Hernández, Padilla-Romo, & Peluffo, 2023). The program eventually reached more than 25,000 schools before being terminated in 2022. We do not expect this program to correlate with battery recycling plant locations, so it is not a threat to our causal estimates.

Public schools account for about 89 percent of the enrollment.[13] By 2013, school enrollment accounted for more than 25 million students across 243,000 schools. This included about 4 million in preschool, 14.1 million in primary education, and 7.3 million in lower secondary education.

The Mexican education system has undergone significant reforms in the last two decades, focusing on improving the quality of teaching and learning and increasing access to education. These reforms have included changes to teacher training and evaluation, introducing new curricula and teaching materials, and developing of standardized tests to assess student learning, such as the National Assessment of Academic Achievement in School (ENLACE) whose data we use here.

3 Data

For our analyses, we rely on the following sources of data.

3.1 Used Lead-Acid Battery Recycling (ULABs) Facilities

To identify the effects of lead exposure from battery recycling we rely on a list of 26 used lead-acid battery recycling facilities in Mexico (see Figure 1 for the location of the plants). These facilities were identified and geo-referenced by Tanaka et al. (2022). The authors identified facilities from three main sources: (1) a report published by the Commission for Environmental Cooperation (Commission for Environmental Cooperation, 2013) (2) from Mexico's Registry of Emission and Transfer of Contaminants, with which plants in Mexican industries that emit select pollutants are required to register;[14] (3), and from a 2014 list

[13]When attending public schools, students usually enroll in the closest one to their homes. Students' parents send a list of three desired schools for preschool and primary school; for secondary education, they send five schools. Then, the schools are assigned based on two criteria: 1) siblings attending the school and 2) household address.

[14]Unfortunately, we cannot use the reported emissions from Registry of Emission and Transfer of Contaminants as a reliable measure of lead emissions from ULAB facilities in Mexico. Environmental organizations have reported that many large recycling facilities do not report to the Registry of Emission and Transfer of Contaminants Gottesfeld et al. (2023). We can confirm this with our checking of the data, finding that many facilities do not report to the registry and, for those that do, the reported emissions data has many irreconcilable errors.

of approved battery recyclers from Mexico's Secretariat of the Environment and Natural Resources. Given this search method, we include only authorized battery-recycling plants in the sample and our analyses will only address lead pollution from these sources and ignore any lead pollution emitted from informal battery recyclers.[15]

3.2 Wind direction

We accessed wind direction data from the Global Wind Atlas.[16] The Global Wind Atlas reports microscale modeled wind climate data at a 3 kilometer resolution grid. For each grid cell the atlas average windspeed and direction. For each of the 26 battery recycling facilities on the list described above, we extracted the 100 meter wind frequency rose data for the grid cell in which the facility lies. These wind frequency roses report how often the wind is blowing from a given direction at 100 meters above ground level. The 360 degrees around a point is divided into 12, 30-degree sectors, and the share of time the wind is blowing a given sector is reported.

3.3 Test Scores from the National Assessment of Academic Achievement in Schools (ENLACE)

Our primary outcomes of interest, math and Spanish test scores, come from a national standardized test, the National Assessment of Academic Achievement in Schools (*Evaluación Nacional del Logro Académico en Centros Escolares* or ENLACE). This test was a nationwide test designed to evaluate students' academic performance in public and private schools. It was a low-stakes test for students, having no influence on GPA, graduation, or admissions to any school. The exam was developed and administered nationwide by the Ministry of Education (*Secreataria de Educacion Publica* or SEP), with oversight from the National Institute of Education Evaluation (*Instituto Nacional para la Evaluacion de la*

[15] In other countries informal recycling, done without regulatory oversight and often located in residential areas, is common and can drastically increase lead exposure (Haefliger et al., 2009; Ericson et al., 2016).

[16] Global Wind Atlas 3.0 is a free, web-based application developed, owned and operated by the Technical University of Denmark (DTU). The Global Wind Atlas 3.0 is released in partnership with the World Bank Group, utilizing data provided by Vortex, using funding provided by the Energy Sector Management Assistance Program (ESMAP). For additional information visit `https://globalwindatlas.info`.

Educacion or INEE). It aimed to provide information on the quality of education in Mexico, measure the effectiveness of educational policies and practices, and offer parents and educators information about the performance of students and schools.

ENLACE was implemented for the first time in 2006 and was administered annually until 2013 to all public and private elementary school students in grades 3 to 6, as well as to students in grade 9.[17] From 2009 to 2013 it was also administered to students in grades 7 and 8 and, from 2008 to 2013, to students in grade 12. The exam tested students in Spanish, mathematics, and a rotating subject. It consisted of 50 to 70 multiple-choice questions per subject applied in 45-min sessions over two days. Questions were designed to evaluate different levels of cognitive complexity, ranging from simple recall of information to analysis and synthesis. The exam was usually administered in April, and the results were disseminated to parents, educators, and schools in August of the same year.

The test itself was designed in the following way. To ensure comparability of scores across different exam versions, SEP first applied a set of questions to all students and a control group. Then, they used a calibration process called Test Equating based on Item Response Theory, which determined scores by the number of correct answers and by which questions were answered correctly.[18] After calibration, the student's scores were standardized on a scale of 200 to 800, with a mean of 500 and a standard deviation of 100 for each subject and grade. This allowed for an accurate comparison of scores across different exam administrations for each subject and grade.

We observe math and Spanish scores for 30,358,688 individual students in 151,884 schools across the country from 2006 to 2013 (a total of 91,707,458 observations). These data correspond to the universe (after removing inconsistent entries) of students who sat for the ENLACE test during this time. See Figure 2 for a plot of the number

[17]The exam was discontinued in 2013 as part of the education reform undertaken by the 2012-18 government.

[18]Test equating is a statistical method that adjusts for differences in the difficulty level of different versions of each exam so that scores are comparable across years. The model considers the level of difficulty, guessing, and discrimination assigning a score for each student.

of students tested in each grade and year. These data, apart from a few exceptions where the exam could not take place for various reasons, corresponds to all students in Mexico who were eligible for the test in a given year.

For each student-year observation the data contains:

- An identifier of the school in which the student was enrolled and took the test;
- A student identifier that is a scrambled version of the student's national identification number, the Unique Population Registry Code (*Clave Única de Registro de Población* or CURP), so we are able to track individual students over time;
- An indicator of the grade in which the student was enrolled at the time of the test; and
- An indicator of the school session, AM or PM, in which the student was enrolled at the time of the test.

3.4 Location of schools

We retrieved the location of all schools in Mexico from the National Institute of Education Evaluation (*Instituto Nacional para la Evaluacion de la Educacion* or INEE).[19] Specifically we downloaded the Comprehensive Assessment Results System (*Sistema Integral de Resultados de las Evaluaciones* or SIRE) database for each state and extracted the GPS coordinates for each school in the database. This database was last updated for the 2016-17 school year, so may not contain schools that were operating during the ENLACE testing period but have since closed.[20]

3.5 Locality and municipality characteristics

For the heterogeneity analysis described in section 4.3.3, we use locality and municipality characteristics from various sources. Localities are the second smallest administrative unit

[19] We downloaded the SIRE database for each state from this url: https://www.inee.edu.mx/evaluaciones/sire/sire-bases-de-datos/. We last downloaded it in July 2023.

[20] The downloaded SIRE database contained location data for 88 percent of the schools that are present in the test score, or ENLACE, data.

in Mexico, just above block, and correspond roughly to a neighborhood. Municipalities are larger administrative units, between localities and states. From the school location data described above, we can link each school to it's corresponding locality and municipality. We get locality and municipality level demographic and socioeconomic information from various statistical archives.[21] The variables we use include adult education levels (years of completed education for individuals older than 15), access to infrastructure (percent of households in locality with access to sewerage), rates of social security access, malnutrition rates, local income inequality (Gini index), and overall marginalization.[22]

4 Estimating the Effects of Lead Exposure on Test Scores

We now come to estimating the average impact of lead-acid battery recycling on students' academic performance. Tanaka et al. (2022) showed that after the US EPA strengthened their air quality standard for lead in 2009, used lead-acid battery exports from the US to Mexico sharply increased relative to previous years. The value-added and output in Mexican battery-recycling plants also increased discontinuously relative to other, similar industries. We investigate the potential effects of this increased battery recycling activity on academic performance in schools close to these recycling plants, where students can be directly exposed to lead contamination primarily through the air and top soil.

4.1 Defining lead exposed students

The gold standard for measuring lead pollution exposure is a biological measure of lead in the body. This can be done via testing blood to measure lead concentrations from recent exposure, e.g. Gazze et al. (in press), or testing bones or teeth, for example

[21] Locality-level measures come from a 2005 population enumeration from Mexico's National Population Council (*Consejo Nacional de Poblaci ón* or CONAPO) (Instituto Nacional de Estadística y Geografía, 2005). Municipality characteristics come from the National Council for Evaluation of Social Development Policy (*Consejo Nacional de Evaluación de la Política de Desarrollo Social* or CONEVAL) and the National Population Council (*Consejo Nacional de Población* or CONAPO) (Consejo Nacional de Poblaci ón (CONAPO), 2005; Consejo Nacional de Evaluación de la Política de Desarrollo Social (CONEVAL), 2005).

[22] The marginalization index is calculated by Mexico's *Consejo Nacional de Población*, or the National Population Council, and uses principal component analysis to create an index of marginalization from measures related to education and illiteracy, housing characteristics (like access to electricity and overcrowding), size of population, and income.

shed baby teeth a la Johnston et al. (2019), to measure longer term lead exposure. These tests provide individual measures of lead exposure. When these measures aren't available, researchers can also use environmental pollution data as a proxy for lead exposure, e.g. Hollingsworth and Rudik (2021). Lead in the air, soil, or water is a likely indicator that populations living, studying, or working in the polluted area have been exposed. Unfortunately, Mexico did not have a lead pollution monitoring network nor did they systematically collect bio-markers for lead exposure during our study period.[23] To overcome this, we rely on the battery recycling facility location, school location, and wind direction data described in Section 3.

The first measure we use to proxy for lead exposure is the distance between battery recycling facilities and the primary and lower secondary schools (i.e. schools where the ENLACE math and Spanish testing took place). We define students as exposed to lead pollution from ULAB recycling in a given year if they attend a school within 2 miles of a battery recycling facility in that year. Figure 3 illustrates this process. In each panel a battery recycling facility is shown as a red point and primary and lower secondary schools are shown as black points. The red circle around the recycling facility has a two mile radius. We define all schools within this red circle as "near" the recycling facility and, therefore, exposed to lead pollution from the facility. This two mile radius is supported by an analysis of battery recycling facilities in the United States, where a network of lead pollution monitors allows us to measure how far airborne lead pollution travels. In Figure 4, recreated from Tanaka et al. (2022), we plot in blue the airborne lead concentrations around more heavily polluting plants in the U.S., i.e. those plants who were required to reduce their pollution to comply with the 2009 updated NAAQS for lead. The figure shows how airborne lead concentrations drop steeply at monitors 3 or more miles from a ULAB facility. The two mile cut-off is also supported by other U.S.-based studies which identify contamination within a 1.5 to a 2-mile radius around airports, where pollution

[23] The 2018 National Health and Nutrition Survey (*Encuesta Nacional de Salud y Nutrición* or ENSANUT) did include blood lead measures for a subset of the population. We are currently in the process of accessing these geocoded exposure measures to validate the location based lead exposure measures we describe below.

comes from leaded aviation fuel, and lead smelters (Miranda, Anthopolos, & Hastings, 2011; Currie, Lucas, Greenstone, & Walker, 2015). This distance from a pollution source as a proxy for exposure has been used by other researchers, e.g. C. L. Persico and Venator (2021), to study many types of toxic pollutant exposure.

We can additionally proxy for lead pollution exposure using wind direction. Environmental scientists have shown that environmental lead concentrations, often tested in top soil, and individual exposure around known lead pollution sites are correlated with prevailing winds (Karali, Stavridis, Loupa, & Rapsomanikis, 2020; Johnston et al., 2019; Zhang et al., 2016; Lidsky & Schneider, 2003). Winds blow the pollution downwind of the source, where it settles in the top soil. Given this, we can further refine our definition of lead exposed students by identifying schools that are both near to a battery recycling facility, as defined above, and downwind of the prevailing winds. We define the prevailing wind direction as the 30-degree sector from which the wind blows the highest percentage of the time. Downwind schools are then considered as those that fall within a 30 degree cone that is directly opposite, plus or minus 180 degrees from, the prevailing wind cone. For example, if the wind most frequently blows directly from the North, the downwind cone would be defined from 165 degrees (15 degrees East of South) to 195 degrees (15 degrees West of South). All schools in this cone are then considered downwind schools. We also test the robustness of this definition to widening the downwind cone. This method focus on lead pollution that is emitted into the air and dispersed by the wind. It ignores other potential pathways of lead exposure, for example through transport routes where lead materials are brought in and out of the facilities, via the clothing of battery recycling facility staff who can bring lead pollution home on the skin, hair, or clothing, or via waterways if waste is dumped or leeches into surface or ground water. Therefore, our comparison of students who attend downwind versus more upwind schools may result in a lower bound estimate of the effect of lead exposure from the post-2009 increase in battery recycling activity, as even students at upwind schools may be exposed to lead pollution from the facility via non-air pathways.

4.2 Empirical Strategy

4.2.1 Main specifications

For our primary analysis, we construct a yearly panel of school-session-grade observations. We calculate the mean standardized Spanish and math test scores as well as proficiency levels, described below, in each school-session-grade. We adopt a difference in difference strategy, where we compare the test score trends over time between session-grades in schools nearby, fewer than 2 miles from, a battery recycling facility and those more than 2 miles from a facility but within the same state. To provide clarity, imagine two primary schools. Each have a morning session where they teach students in grades 3 to 6. School A is 1 mile from the nearest recycling facility. School B is 5 miles away from the same facility. Both schools are small enough to only have one classroom per grade. In this method we would identify the effect of the post-2009 increase in lead pollution from the recycling facility by comparing the 3rd grade classroom's test scores at School A with those at School B before and after the 2009 U.S. policy change.

Empirically, this method translates to the following specification:

$$y_{segt} = \alpha_{s\times e\times g} + \delta_t + \gamma_{p(s)\times t} + \beta(Near_s \times Post_t) + \varepsilon_{segt} \tag{1}$$

where y_{segt} represents a test score outcome for school s - session e - grade g in year t. We evaluate two outcomes for math and Spanish: the average standardized ENLACE test score[24] and the percentage of students proficient in each subject.[25] $Near_s$ is a dummy variable that equals one if school s is located within two miles from the nearest

[24] We first standardized student's test scores by grade and year, then we take the average of these test scores in each school-session-grade-year.

[25] Proficiency is evaluated in four achievement levels. Level 4 contains the highest-achieving students, while level 1 contains the lowest. We define students in levels 3 and 4 as proficient.

lead-recycling plant $p(s)$, and zero if the school s is farther away from it – 502 schools are within this two mile distance from a recycling facility. The $Post_t$ indicator takes the value 0 before 2009 and the value 1 in 2009 and thereafter. The terms $\alpha_{s\times e\times g}$ and δ_t represent school-session-grade and year fixed effects respectively, making this a two-way fixed effects specification that accounts for common shocks in any year and time-invariant differences across classrooms. Additionally, in our preferred specification, we include plant-by-year fixed effects, $\gamma_{p(s)\times t}$. These fixed effects account for differential trends in school-session-grades' achievement around each plant, essentially accounting for the fact that schools around, for example, a plant in an urban area may be fundamentally different and evolve differently over time than schools around plants in a more rural area. In the results below we also test the robustness of our results to varying fixed effects. For example, we can include a grade g by year t fixed effect that allows test scores trends to vary by grade. Our coefficient of interest is β, which captures the differential effect of increased lead exposure due to the U.S. environmental regulation on test scores at schools within 0–2 miles from the closest battery-recycling plant. We restrict our analysis to school-session-grades that we observe at least once before 2009 and at least once in 2009 or later. Standard errors are clustered at the school level, as this is the level at which the lead exposure indicator is defined.

The identification assumption is that in the absence of this 2009 policy change and conditional on the fixed effects included, classrooms near and far from their closest plant would have exhibited parallel trends in test scores. We test how plausible this assumption is by running event studies of the form:

$$
\begin{aligned}
y_{segt} = \alpha_{s\times e\times g} + \delta_t + \gamma_{p(s)\times t} + \sum_{\tau=2006}^{2008} \beta_\tau (Near_s \times \mathbb{1}(t=\tau)) + \\
\sum_{\tau=2010}^{2013} \beta_\tau (Near_s \times \mathbb{1}(t=\tau)) + \varepsilon_{segt}
\end{aligned}
\tag{2}
$$

where β_τ captures the effect of being close to a battery-recycling plant on students' scores τ periods before or after the US environmental reform. This specification allows us to test directly if there are any differential trends before 2009, which would suggest that the parallel trends assumption may be violated. We expect all the β_τ's in the pre-2009 years to be indistinguishable from zero, which would be consistent with the parallel trends assumption.

4.2.2 Addressing other identification concerns

The primary threat to our identification comes from time varying changes other than lead pollution that may be affecting schools close to battery recycling facilities deferentially relative to those farther away. One such concern is increased economic activity. The ramp up of ULAB recycling activity after 2009 likely also caused an increase in employment at these plants, not just an increase in lead pollution. These economic effects are likely stronger in areas closer to plants. While we do not observe employment at the facilities, so cannot directly test for this, we do see that schools within two miles of a recycling facility grow by 5-10 students after 2009, compared to schools farther away. This could reflect families moving into the area to take advantage of job opportunities, and this change in student composition could be driving the effects we estimate. We can address this concern in two ways.

First, we can use wind direction to differentiate between upwind and down wind schools. To do this we define a specification that is similar to equation 1, but interacting the *Near* indicator with an indicator equal to 1 if a school is downwind from, as described in Section 4.1, a battery recycling facility. The environmental science literature has shown that lead pollution moves with prevailing winds, but we do not expect the economic effects of a post-2009 ramp up at a recycling facility to varying based on bearing from a plant relative to prevailing winds. In this specification the exposed group is made up of those schools where students are exposed to both the increased pollution and economic activity, whereas the non-exposed group, including nearby upwind schools, is made up of students who are exposed to the change in economic activity but not, or at least relatively less, exposed to the lead pollution.

We can also take advantage of the student-level data to account for migration that may be happening in response to the 2009 U.S. policy change. This could be both families moving towards battery recycling facilities because of increased labor demand or families moving away in response to increased pollution. To test if this migration is driving our results, we use a similar specification in equation 1, but our unit of observation here is an individual. We compare changes in test scores before and after 2009 between students studying in schools near versus farther from recycling facilities. We specify the following equation:

$$\begin{aligned} y_{it} = \theta_i + \delta_t + \kappa_g + \gamma_{p(s)\times t} + \chi[(Near_{ist} \times Post_t \times \mathbb{1}(t < 2009)) + \\ (Near_{is2008} \times Post_t \times \mathbb{1}(t \geq 2009))] + e_{it} \end{aligned} \tag{3}$$

where y_{it} is individual i's standardized math or Spanish test score in year t.[26] In similar fashion to the main specification, we include individual, θ_i, and year δ_t fixed effects. To account for learning as students move up in grade and differences in the ENLACE test between grades we include a set of grade fixed effects, κ_g. We again include a set of nearest plant by year fixed effects to account for areas around battery recycling facilities changing differently over time. Our coefficient of interest is χ. In this specification, the *Near* indicator can vary over time as students, unlike schools, can move locations. This set up also allows us to include grade 7 and 8 test results in our estimation, as we only need to observe students, not specific school-session-grades, both before and after 2009.

We use this specification to account for migration by "freezing" the value of $Near_{ist}$ for each student in 2008, the year before the U.S. policy change was enacted. In other words, whatever the value of the indicator was for a student in 2008, we force to the indicator to maintain that value for all subsequent years. To illustrate, imagine a student attending a

[26]Test scores are standardized at the year-grade level.

school greater than 2 miles from a battery recycling facility as of 2008. If that student moves to a school near a recycling facility as of 2009, the $Near_{is2008}$ indicator for this student will continue to take the value 0 in this specification. This is similar to an intent to treat set up where, no matter what families may endogenously choose to do, they remain in the comparison group that they were in prior to the policy change.

4.3 Results

4.3.1 Estimates of the effect of post-2009 used lead acid battery recycling on test scores

We will first discuss the findings of our main specification, equation 1, presented in Table 2. In Panel A, columns 1 and 2, we estimate that the 2009 U.S.-induced increase in battery recycling activity decreased math test scores by about 0.09 standard deviations (σ) in session-grades at schools within 2 miles of a used lead acid battery recycling activity, relative to session-grades at schools farther away but in the same states. Panel B of the table presents the results of similar specifications, with mean standardized Spanish scores as the outcome. Here we see that the estimated effect is still negative, -0.07σ, though slightly smaller for Spanish than math.

In columns 4 and 5 of each panel we include the plant-, or facility-, by-year fixed effects, and results are qualitatively similar though the magnitude of our estimates decreases. These estimates provide evidence that the negative effects are not driven by differential time trends in school-session-grade's achievement around each plant.

A causal interpretation of these estimates primarily relies on the parallel trends assumption that, in the absence of the 2009 increase in recycling activity, test scores at session-grades near a recycling plant would have evolved parallel to those farther away. To support this assumption we estimate the event study specified in equation 2, with results presented in Figure 5. For both the math and Spanish results, we do not estimate any differences, conditional on the fixed effects specified in 2, between trends in test scores at school-session-grades within 2 miles of a facility versus those farther. This lack of pre-trends is consistent with the parallel trends assumption; lending support to our causal interpretation of the coefficients in Table 2.

Finally, we analyze the effects on students' proficiency in both subjects. Proficiency is evaluated in four achievement levels. Level 4 contains the highest-achieving students, while level 1 contains the lowest. We define students in levels 3 and 4 as proficient students. Columns 1 and 2 of Table A3 show the percentage of students in each school-grade who are proficient in math and Spanish, respectively. The coefficients in these columns suggest that the percentage of students who are proficient decreases by about 2 points in both math and Spanish, from a baseline of 34 and 32 percent, respectively.

4.3.2 Sensitivity checks

Any remaining potential threats to the causal interpretation of the estimates reported in Table 2 must mimic the variation caused by the 2009 U.S. environmental regulation and differentially affect schools located two miles from a lead recycling plant compared to those farther away. As discussed in section 4.2.2, the increased industrial activity after 2009 at these battery recycling plants could have caused other changes besides increases in pollution. One concern is the ramp up in recycling activity also increased labor demand and, potentially, had other effects on local economies. It is not unreasonable to think that these effects may also be correlated with proximity to the plants, felt more strongly in neighborhoods that are closer to the facilities. While we would expect that increases in local economic activity would increase test scores, we do want to confirm that the results we report above are not being driven by these potential changes. To do this we further refine our group of exposed schools to only include those that are near *and* downwind of a recycling facility, as described in 4.2.2.

Table A2 presents the results of this estimation. Focusing on "Panel A: Math scores" we can see that the estimated coefficients are again negative and fall between -0.08 and -0.11 standard deviations. When we define downwind schools as those that fall within a 30°cone of the downwind direction, results are not statistically significant, likely due to the fact that this greatly reduces the number of schools in the "near" group. Expanding the cone to 90°increases the number of schools and the significance of our estimates without greatly changing the point estimate. We see the same consistency in results with the Spanish test scores.

Another, similar concern is that these local changes in pollution and/or economic activity could induce migration. The school-session-grade level estimates we've presented so far do not account for this migration. Given that academic achievement can be partially determined by wealth, e.g. if wealthier families can afford tutoring or their children do not need to work after school to earn income, the negative effects that we've present so far could be driven by migration. This could be the case if high income families move away from battery recycling plants after 2009 to escape increased pollution levels or if low income families may in for job opportunities. We can account for this migration by doing our analyses at the individual level, where can observe students moving schools over time. The results are very similar to the school-session-grade estimates (see Table 3) and do not change when we take the intent to treat approach outline in equation 3, not allowing for potentially endogenous movement of students in response to the 2009 increase in battery recycling.

4.3.3 Dynamic and heterogeneous effects

The event study results that we presented earlier not only support the parallel trends assumption but can also shed light on how the effects of the point-2009 increase in recycling activity change over time. Figure 5 illustrates the negative effects we've presented. These figures also shed light on how effects evolve, with the negative estimated effect of the battery recycling plants getting worse over time for both math and Spanish test scores. What could be driving this worsening of effects? One explanation is that the battery recycling industry continued to experience growth after 2009. This is supported by Tanaka et al. (2022), where they show that used lead acid battery exports from the U.S. to Mexico increased in 2009 and continued to grow in the following years. It could be the case then that lead pollution levels around Mexico's battery recycling plants are getting worse each year after 2009.

A second explanation is that the age at first exposure matters. The younger a child is the weaker their blood-brain barrier, which allows ingested lead to more easily enter their brains (Saunders, Liddelow, & Dziegielewska, 2012). In addition, smaller children are more likely to ingest lead from top soil when they are playing outside (Rees & Fuller, 2020). We can use our school-session-grade level analysis to investigate this, and compare how effects change with age at first exposure, while holding duration of exposure constant. Figure 6 illustrates the results of this analysis on math test scores. Consider Panel A, which plots the results of the event study described in equation 2 but only for school-sessions in grade 3. Here we can see that negative effects start to appear in 2012. Third graders in 2012 would have been in kindergarten in 2009 and, if studying in a school near a recycling plant, have been exposed to the post-2009 pollution for 3 years. Compare this to grade 4's results in Panel B, focusing again on 2012. These fourth graders had also been exposed to three years of post-2009 pollution, but were slightly older, in grade 1, in 2009. For fourth graders we estimate a smaller, less negative, effect of being near a battery recycling plant in 2012. We see a stronger effect for fourth graders in 2013. These fourth graders were in kindergarten in 2009, the same age of exposure at which we saw effects among the third graders. Since the ENLACE test was ended in 2013, we cannot observe younger cohorts, but the grade 5 and 6 event studies, where all children were in grade 1 or later as of 2009, continue the a similar pattern. These grade-specific event studies, while not conclusive given large confidence intervals, suggest that age at first exposure matters with respect to lead exposure's effect on learning.

The dynamic and age-based heterogeneity discussed above consider how effects may changed based on the amount and severity of lead exposure. We are also interested in exploring how family, community, and institutional factors mitigate the lead exposure - learning relationship. To test for heterogeneity along these lines, we use the locality and municipality level data described in section 3.5. We consider how our estimated effects vary based on pre-2009 characteristics, including adult educational achievement, access to infrastructure, malnutrition rates, formal employment status, regional income inequality, and marginalization. To do this we first define a set of indicator variables equal to one if a classroom is in a community with an above median value of each characteristic. The median we consider is the 50-th percentile of each measure among all classrooms within a 2-mile radius of a battery recycling facility. To estimate if effect sizes vary for classrooms in the above versus below median groups for a given characteristic, we fully interact the above indicator with the specification in equation 1.

The results of these analyses are presented in Table 4. For ease of interpretation we first estimate equation 1 separately for the above and below median classrooms. For example, Panel A Column 1 shows that the post-2009 increase in recycling negatively affected math test scores by -.12 standard deviations for students attending schools in relatively less educated communities, measured as average years of schooling completed by adults in the community. We estimate a null effect in schools with above median educational attainment. The row ”Difference (high - low)” presents the estimated coefficient on the interaction between ”Near facility X Post-2009” and the above median indicator, showing the difference between the coefficients presented in columns 1 and 2 and testing the statistical significance of that difference.

In Panel A of table 4 we consider characteristics that are signs of more developed, wealthier, or generally better off communities. In each case we find that the negative effects of lead are stronger in communities with relatively low values of these characteristics. The differences are statistically significant in the case of education achievement and formal employment, proxied for here by the share of the community that is covered by a social security agency. In communities with lower quality infrastructure, which we measure as the percentage of households who are connected to a sewer, effects are again strong relative to higher access communities, but there is not a statistically detectable difference in the effect sizes. In Panel

B we see the opposite trend, as the measures we consider here take higher values in worse off communities. In each case we find that, qualitatively, the effects of the lead pollution we study are higher in communities above the median of these characteristics. The differences in effects are strongest and statistically different when comparing communities above and below the median value of the marginalization index. Taken together these results tell a consistent story, that the negative learning effects of pollution exposure are concentrated in communities that were already worse off before the 2009 increase in recycling activities.

5 Discussion

How can we contextualize the magnitude of the effects that we estimate? One way is to compare our estimates to the effects of policies aimed at increasingly educational attainment. A recent review of education intervention impact evaluations in low- and middle-income countries found that, at the median, these interventions are shown to increase learning outcomes by 0.10 standard deviations. These interventions include programs aimed at both increasing access to education and in-classroom learning. An education intervention with this effect size could reverse the effects of lead pollution in our setting (Evans & Yuan, 2022). From Mexico, a study examining the effect of a program to increase the time students spend in the classroom, found that full-time school increased test scores by 0.11 standard deviations (Cabrera-Hernández, 2020). Effects of this program were concentrated among poorer students, who may be similar in ways to those in our study living in marginalized communities around lead acid battery recycling facilities. Unfortunately, this program was shut down in 2022 (Mexico News Daily, 2022).

We can also place a monetary value on our estimates by calculating how the lower test scores that result from the post-2009 increase in recycling activity will affect students' future earnings. For this exercise we consider the total costs in terms of lifetime earnings to a cohort of students living near a ULAB recycling plant in the years after 2009. Consider the cohort of students who were in 3rd grade in 2009. In 2009 average annual wages in

Mexico was 18,806 USD in 2016 dollars (OECD 2023). Using a discount rate of 5 percent, the 2009 present value of future earnings for a 3rd grader in Mexico is 208,705 USD.[27] We can next apply estimates from Mexico and other countries to link test scores to future earnings. De Hoyos, Estrada, and Vargas (2021) link grade 12 test scores to young adult earnings for secondary school graduates in Mexico and find that a one standard deviation change in test scores in associated with a 6% change in earnings. Chetty et al. (2014) and Lindqvist and Vestman (2011) do similar analyses in the U.S. and Sweden and estimate relationships between 6 and 15%, relative to a 1 standard deviation change in test scores. If we apply our most conservative estimates of the effect on math scores from Table 2, -0.08 standard deviations, we estimate that the post-2009 growth in ULAB recycling reduced lifetime earnings of each 3rd grader by between 1,002 and 2,504 USD.[28] Given that 15,553 3rd graders studied within two miles of a ULAB recycling plant in 2009, the total estimated cost to them in terms of lifetime earnings is 15.6 to 38.9 million USD. Each year a new cohort of students is born into the communities surrounding ULAB recycling plants, and these children additionally bear this cost. Thus we consider this cost an annual cost of pollution from the post-2009 increase in ULAB recycling. We consider this estimate to be a lower bound of the cost given that lead pollution exposure is especially harmful to young children. In this case we expect that the lost lifetime earnings per cohort would increase past the time span we observe in our data. This cost estimate is additionally a lower bound given that it ignores other health related effects of lead pollution exposure, including negative effects on cardiovascular and renal health.

Estimates of the costs of reducing lead pollution emissions from ULAB recycling activities comes from Burr, Lazzari, and Greene (2011), who estimated that the cost of bringing the 14 ULAB recycling plants in the U.S. into attainment with the updated 2009 air quality

[27]We apply the 5% discount rate following Chetty, Friedman, and Rockoff (2014). We do not consider wage growth here, as the average wage growth in Mexico between 1991 and 2022 was very small, on average 0.3% (OECD, 2023). If we consider this then lifetime expected earnings are 210,257 USD.

[28]We use the range of test score to future earning relationship estimates here given that the Mexico estimate is based only on secondary school graduates and considers their earnings at ages 18-20. We believe this can underestimate the relationship as it ignores students who have not completed secondary school, which is a large share in Mexico, and thus are likely earning significantly less.

standards was 10.33 million USD per year in 2016 dollars. If we assume it would cost the same amount to clean up pollution from processing the exported batteries in Mexico, then the annual benefits of reducing emissions clearly outweigh the costs. If we increase this cost estimate to account for the 26 recycling facilities in Mexico, assuming that costs are more a function of the number of facilities as opposed to the number of batteries processed, the costs increases to around 19.2 million USD, still well within range of the total value of lost lifetime earnings estimated above.

6 Conclusion

In this paper we estimate the impact of increased lead acid battery recycling on the academic performance of students in Mexico. This increased activity of a heavily polluting industry in Mexico is a result of a 2009 U.S. policy change that tightened environmental standards for lead and caused the industry to shift activities to Mexico, where regulation remained less stringent.

For our analyses we use data from ENLACE, a census-based standardized exam in Mexico, and a difference-in-difference approach comparing students at schools close to versus farther away from Mexican battery recycling plants before and after 2009. We find that exposure to the post-2009 lead-battery recycling reduces academic achievement in math by 0.05-0.09 standard deviations. Effects on Spanish scores are also negative and slightly smaller. We complement these results with event study estimates, which provide support for the parallel trends assumption necessary for identification of causal effects. The event study estimates also show that the negative effect of lead exposure on test scores persists for at least 4 years after students were first exposed to the 2009 increase in lead pollution. In fact, the effects seem to become even more negative over time. We also show suggestive evidence that age at first exposure matters, with students who were in kindergarten or younger as of 2009 experiencing stronger effects than those who were older. These results are robust to school- and student-level specifications and are not driven by other local changes that could have accompanied the post-2009 growth in Mexico's battery recycling industry such as availability of jobs or migration.

We take advantage of a seldom available comprehensive dataset on national standardized test scores in a developing country and implement a quasi-experimental research design. Our findings highlight the harmful impact of lead exposure on academic performance in the context of limited regulatory oversight. Understanding the effects of exposure to pollution on children's cognitive development is especially important in developing countries, where citizens have fewer resources to adapt to worsening environmental quality and where parents have fewer resources to make compensatory investments. It is difficult to directly compare our results to other studies from rich settings, as we do not know the magnitude of lead pollution exposure changes that are driving our results. Still, our heterogeneity analyses show that the negative results of this post-2009 increase in recycling activity are concentrated in communities that are already worse off before the policy change. For example, effects are stronger in communities with lower levels of adult education, less access to infrastructure, and higher malnutrition rates. These findings suggest that cost of exposure estimates from rich settings many underestimate effects in less developed settings, where the vast majority of lead pollution exposure today occurs. Our findings underscore the importance of continued research on the impact of environmental factors on child development in low- and middle-income countries.

Our findings also have important implications for environmental and education policy. First, our analyses build on Tanaka et al. (2022), further quantifying the size of the environmental externality from ULAB recycling shifting from the U.S. to Mexico and underscoring the importance of transboundary coordination of environmental policy. From an education perspective, because we study the impact of lead exposure on academic outcomes during schooling years (rather than during early childhood or gestational periods), the results of this study underscore the importance of investing in compensatory measures to protect students from exposure to pollution in schools.

Our estimated effect sizes are largely in line with the literature linking pollution and test scores. Compared to studies that consider air pollution, usually defined as PM10 or PM2.5, our estimated effects are slightly larger. Studies that estimate the effects of day-of-test particulate matter pollution on test score outcomes find a negative effect of 0.03 to 0.05 standard deviations, with effects being stronger for more analytical subjects like mathematics (Amanzadeh, Vesal, & Ardestani, 2020; Ebenstein, Lavy, & Roth, 2016). Looking at the effects of longer-term, at-school exposure to air pollution from vehicle traffic, Heissel, Persico, and Simon (2019) find that attending schools downwind of a major highway is associated with a 0.04 standard deviation decrease in test scores. In a U.S.-based study linking lead exposure and education, where the authors were able to use blood lead level (BLL) testing data to measure lead exposure precisely, the authors found that interventions to decrease BLLs resulted in a 0.12 standard deviation increase in educational performance, compared to those students who were not eligible for the intervention (Billings & Schnepel, 2018). If implemented in our settings, these same interventions could potentially reverse the negative impacts of lead pollution exposure that we estimate here.

Despite decades of research showing the negative health effects of lead pollution, global exposure rates remain unbelievably high (Rees & Fuller, 2020). And the vast majority of the costs of this lead pollution exposure falls on children living in low- and middle-income countries (Larsen & Sánchez-Triana, 2023; Crawfurd, Todd, Hares, Sandefur, & Bonnifield, 2023). Rich countries have and continue to work hard to clean lead out of their environments, but, like in the setting we studied here, these environmental policies have at times worsened the problem in LMICs by shifting pollution sources to areas with weaker or less enforced regulatory standards. There is still much work to be done to combat this environmental challenge and reduce the global costs of lead pollution exposure.

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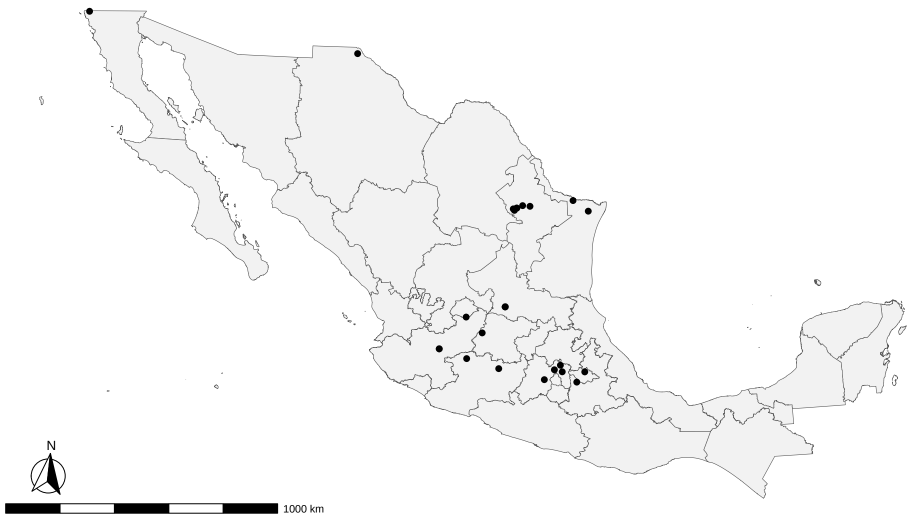
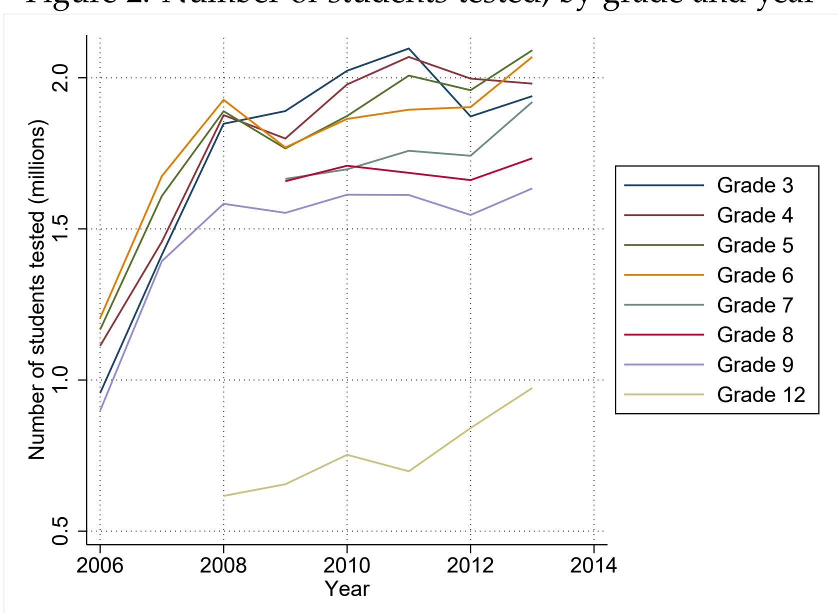
Figure 1: Used Lead Acid Battery Recycling Facilities in Mexico



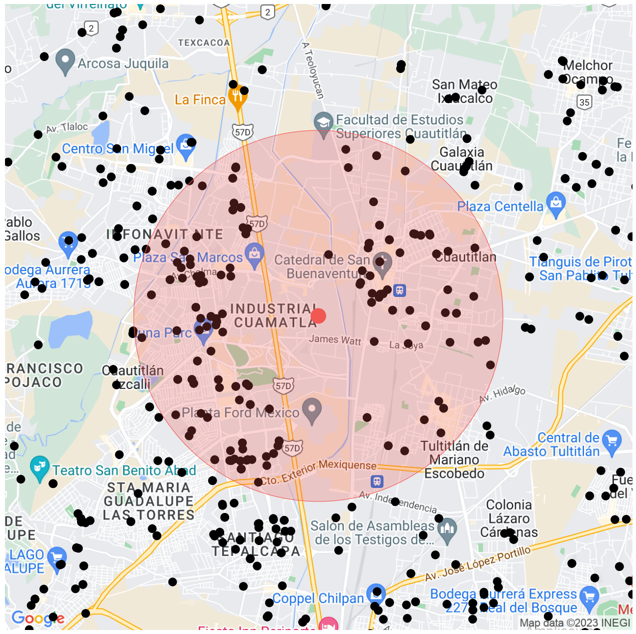
Note: The 26 facilities locations plotted here as black points were compiled by Tanaka et al. (2022) from the CEC and SEMARNAT. Some facilities are located very close to each other so difficult to visually differentiate at this scale. This map was produced in R using ggplot.

Figure 2: Number of students tested, by grade and year

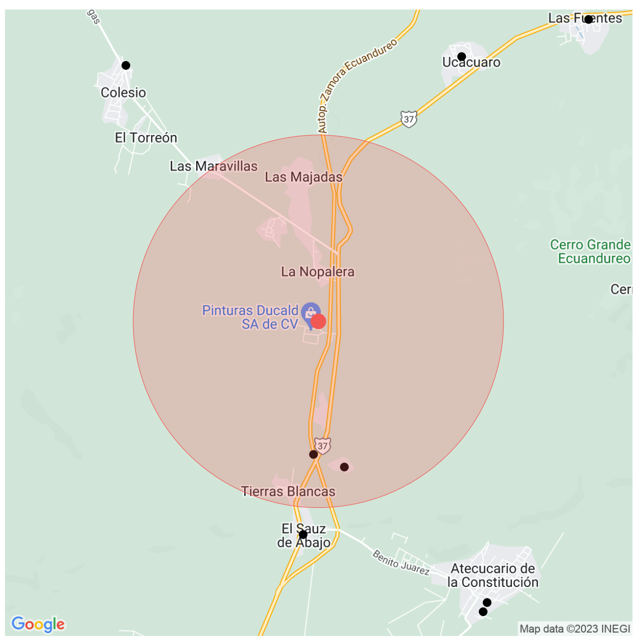


Note: Here we plot the number of students for whom we observe ENLACE test results, by grade and year. Note that tests for grades 7 and 8 did not start until 2009 and testing in grade 12 did not start until 2008.

Figure 3: Identifying lead exposed schools



(a) Panel A: Used lead acid battery recycling facility and nearby schools in Greater Mexico City



(b) Panel A: Used lead acid battery recycling facility and nearby schools in a rural part of Michoacán State

Note: TUsed lead acid battery recycling facilities are indicated by a red point. Black points indicate schools at which the ENLACE test was conducted between 2006 and 2013. The red circle represents a two mile radius around the recycling facility. Maps were generated in R using ggmap.

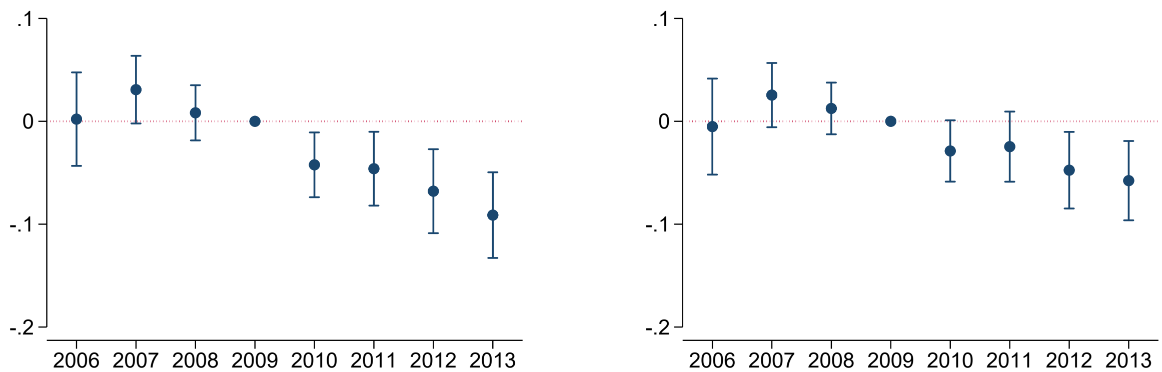
Figure 4: Lead concentrations near U.S. ULAB battery recycling facilities

Note: This figure, replicated from Tanaka et al. (2022), plots the average ambient lead concentration at monitors within 10 miles of a U.S. lead acid battery plant, in 1 mile bins. The figure only includes monitors around more heavily polluting plants, which are defined as those around which ambient lead concentrations are greater than 0.15 micrograms per cubic meter before the 2009 regulatory change, i.e. for whom the updated standard is "binding." The data on battery recycling plant location comes from the U.S. Toxic Release Inventory and the lead concentration data come from the U.S. Environmental Protection Agency.

Figure 5: Effects of being close to a lead-acid battery recycling plant on scores, by year

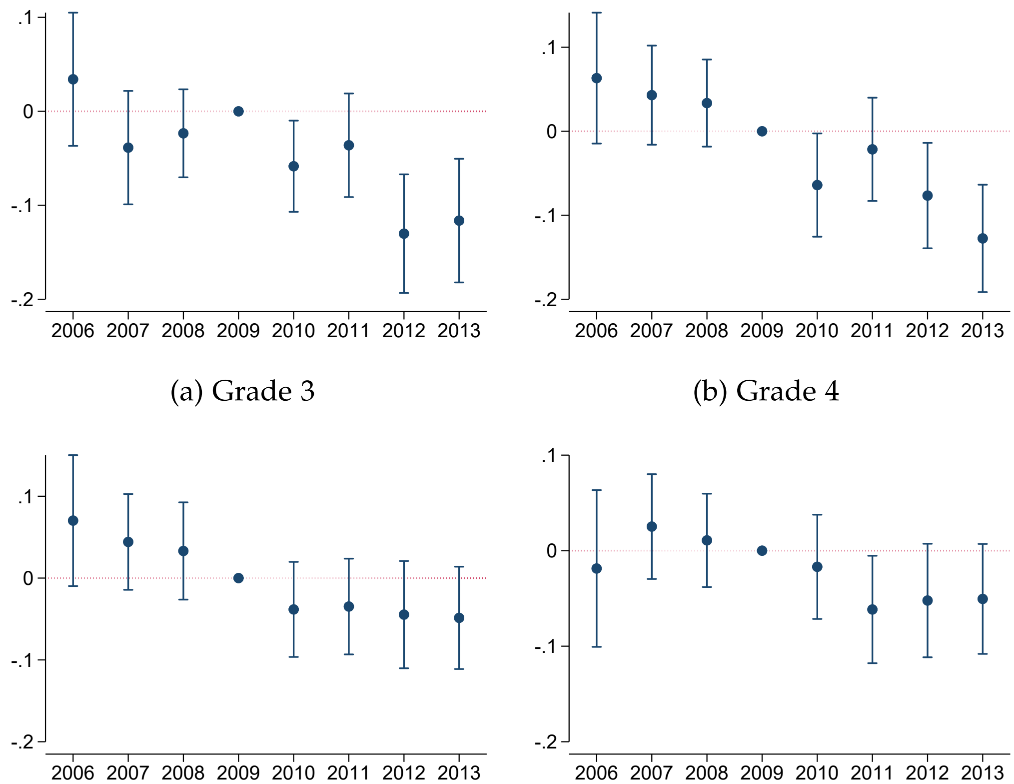
Panel A: Math Scores

Panel B: Spanish Scores



Notes: Figure displays the coefficients and 95% confidence intervals from the event-study of being near a recycling plant when looking at math and Spanish scores as outcomes. These coefficients correspond to the β_τ parameters in equation 2. Standard errors are clustered at the school level. The reference period is 2009 when the US changed its lead air quality standard.

Figure 6: Event study of math scores, by grade



(a) Grade 3

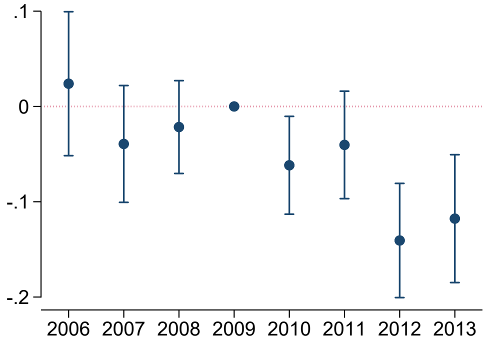
(b) Grade 4

(c) Grade 5

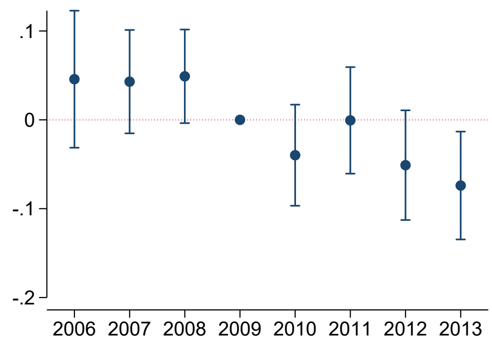
(d) Grade 6

Note: This figure plots the results of four event studies, estimated on standardized math test score results separately for school-grade-sessions in grade 3-6. Each panel plots the point estimates and 95% confidence intervals of the β_τ *parameters from equation 2, estimated separately for each grade.*

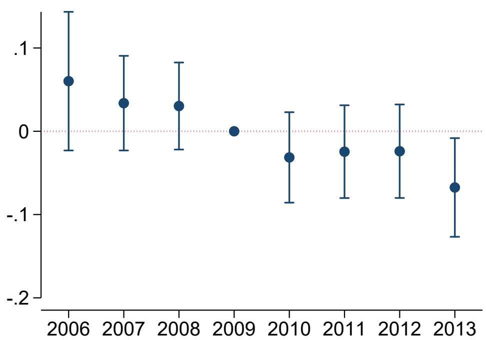
Figure 7: Event study of Spanish scores, by grade



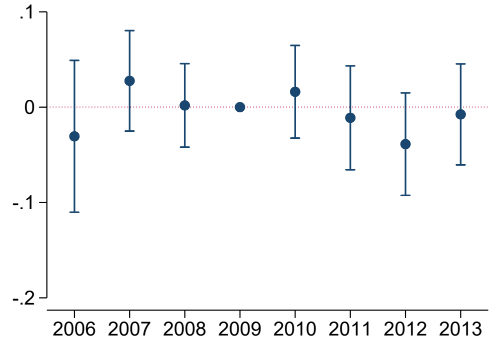
(a) Grade 3



(b) Grade 4



(c) Grade 5



(d) Grade 6

Note: This figure plots the results of four event studies, estimated on standardized Spanish test score results separately for school-grade-sessions in grade 3-6. Each panel plots the point estimates and 95% confidence intervals of the β_τ *parameters from equation 2, estimated separately for each grade.*

Table 1: Summary Statistics: Test Scores

	Grade 3	Grade 4	Grade 5	Grade 6	Grade 9
Panel A: Math					
Mean	539.26	534.84	535.61	543.03	526.23
	(122.71)	(90.24)	(122.81)	(124.44)	(115.62)
Proficiency Rate (%)					
Non-satisfactory	17.94	19.40	18.81	17.61	18.81
Basic	41.24	42.10	42.99	40.69	47.89
Good	26.78	24.46	24.21	25.98	22.31
Excellent	14.04	14.04	13.99	15.72	10.99
Observations	14,039,726	14,270,661	14,361,452	14,305,880	11,833,328
Panel B: Spanish					
Mean	538.10	526.96	526.19	531.28	505.17
	(112.90)	(117.93)	(110.10)	(111.57)	(105.65)
Proficiency Rate (%)					
Non-satisfactory	15.79	19.99	17.96	17.22	21.59
Basic	41.57	41.94	44.15	42.60	47.64
Good	33.34	28.88	30.58	32.18	26.87
Excelent	9.31	9.19	7.31	8.00	3.90
Observations	14,047,767	14,256,445	14,343,142	14,283,435	11,834,961

Notes: Mean non-standardized ENLACE test scores for each subject and grade are reported. Test scores represent exams taken between 2006 and 2013. Standard deviations are in parenthesis. The total number of students tested in each grade between 2006 and 2013, by subject, are reported in the ”Observations” rows. In addition we report the share of students in the same range of years that fall into each proficiency category, by grade and subject.

Table 3: Effect of increased battery recycling activity on students attending school close to a recycling facility, individual-level results

				Intent-to-treat	
	(1)	(2)	(3)	(4)	(5)
Panel A: Math scores					
Near facility X Post 2009	-0.0815***	-0.0892***	-0.0821***	-0.0813***	-0.0772***
	(0.0119)	(0.0126)	(0.0125)	(0.0110)	(0.0114)
Observations	42,003,229	42,003,229	42,003,229	21,570,694	21,570,689
R^2	0.704	0.707	0.708	0.692	0.696
N clusters	55,770	55,770	55,770	50,981	50,978
Panel B: Spanish scores					
Near facility X Post 2009	-0.0541***	-0.0682***	-0.0604***	-0.0567***	-0.0591***
	(0.0110)	(0.0109)	(0.0108)	(0.00975)	(0.0100)
Observations	41,984,199	41,984,199	41,984,199	21,557,200	21,557,195
R^2	0.718	0.720	0.720	0.707	0.709
N_clust	55,771	55,771	55,771	50,985	50,982
Fixed effects:					
Individual	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓
Grade	✓	✓	✓	✓	✓
Grade-by-year	✓	✓	✓	✓	✓
Municipality		✓	✓		✓
State-by-year		✓	✓		✓
Plant-by-year			✓		✓

Note: The unit of observation is the student-year. Near is a dummy variable that equals one if the student attends a school s located within two miles from the nearest lead-recycling plant $p(s)$, and zero if their school s is farther away from it but in the same state. In columns 4 and 5, Near is defined using the 2008 value for each student, as discussed in section 4.2. The $Post_t$ indicator takes the value 1 in 2009 and thereafter. Outcomes are students' standardized test scores, standardized at the grade-year level. Panel A reports estimates with math scores as the outcome; Panel B reports estimates with Spanish test scores as the outcome. In each column the two specifications, with math and Spanish as outcomes, include the same levels of fixed effects; only the outcomes are changed. Standard errors, in parentheses, are clustered at the school level. * p<0.1, ** p<0.05, *** p<0.01.

Table 2: Effect of increased battery recycling activity on students attending school close to a recycling facility

	(1)	(2)	(3)	(4)	(5)
Panel A: Math scores					
Near facility X Post 2009	-0.0936***	-0.0890***	-0.0881***	-0.0707***	-0.0663***
	(0.0136)	(0.0137)	(0.0140)	(0.0141)	(0.0142)
Number of students					-0.000889***
					(0.0000655)
Observations	1,141,093	1,141,093	1,141,093	1,141,093	1,141,093
R^2	0.516	0.517	0.523	0.525	0.526
Num. of clusters	48,830	48,830	48,830	48,830	48,830
Panel B: Spanish scores					
Near facility X Post 2009	-0.0674***	-0.0637***	-0.0639***	-0.0559***	-0.0539***
	(0.0126)	(0.0127)	(0.0127)	(0.0126)	(0.0127)
Number of students					-0.000409***
					(0.0000599)
Observations	1,141,007	1,141,007	1,141,007	1,141,007	1,141,007
R^2	0.560	0.561	0.565	0.567	0.567
Num. of clusters	48,829	48,829	48,829	48,829	48,829
Fixed effects:					
School-session-grade	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓
Grade-by-year		✓	✓	✓	✓
Session-by-year		✓	✓	✓	✓
State-by-year			✓	✓	✓
Plant-by-year				✓	✓

Note: The unit of observation is school-session-grade-year. Near is a dummy variable that equals one if school s is located within two miles from the nearest lead-recycling plant $p(s)$, and zero if the school s is farther away from it but in the same state. The $Post_t$ indicator takes the value 1 in 2009 and thereafter. The sample includes all school-sessions in grades 3, 4, 5, 6, and 9 which we observe at least once in the pre-2009 and at least once in the post-2009 period. Outcomes are school-session-grade means of students' standardized test scores, standardized at the grade-year level. Panel A reports estimates with math scores as the outcome; Panel B reports estimates with Spanish test scores as the outcome. In each column the two specifications, with math and Spanish as outcomes, include the same levels of fixed effects (as indicated in the bottom panel); only the outcomes are changed. Standard errors, in parentheses, are clustered at the school level. * p<0.1, ** p<0.05, *** p<0.01.

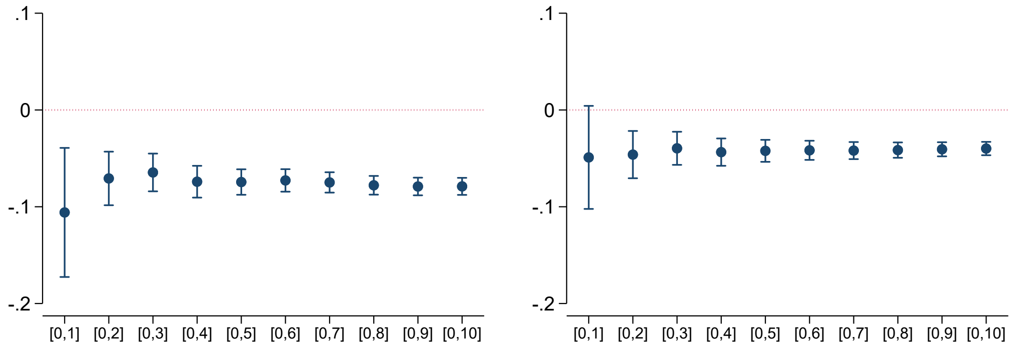
Table 4: Effect of attending school close to a battery recycling facility, by community characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Low	High	Low	High	Low	High
Panel A	Education (years)		Access to sewer(%)		Social security (%)	
Near facility X Post 2009	-0.124***	0.0117	-0.0613***	-0.0313*	-0.119***	-0.00783
	(0.0223)	(0.0157)	(0.0221)	(0.0173)	(0.0220)	(0.0187)
Difference (high - low)	0.136***		0.030		0.111***	
	0.0273		0.0281		0.0289	
Observations	835,657	286,623	603,431	519,001	773,619	348,813
R^2	0.488	0.587	0.474	0.547	0.512	0.555
Num. of clusters	36,241	11,714	26,350	21,612	33,918	14,044
Panel B	Marginalization index		Gini index		Malnutrition rate	
Near facility X Post 2009	-0.0272*	-0.0906***	-0.0680***	-0.0802***	-0.0302*	-0.0660***
	(0.0155)	(0.0245)	(0.0218)	(0.0182)	(0.0177)	(0.0205)
Difference (high - low)	-0.0634**		-0.012		-0.036	
	0.0291		0.0284		0.0271	
Observations	282,578	857,479	426,471	713,586	218,510	921,547
R^2	0.579	0.497	0.514	0.533	0.561	0.510
Num. of clusters	11,341	37,449	18,552	30,238	8,638	40,152

Note: The estimates in this table are produced using the same specification as the estimates presented in Table 2, column 4, with the mean standardized math scores as outcomes. The specification is run separately on schools in communities with above and below median values of the given characteristics, with medians calculated from among schools within two miles of a battery recycling facility. The "Difference" row is estimated by fully interacting the Table 2, column 4 specification with an above median indicator for each characteristic. This row reports estimates of the coefficient on the interaction between this indicator and the "Near X Post" term. Standard errors are clustered at the school level. * p<0.1, ** p<0.05, *** p<0.01.

A Additional Table & Figures

Figure A1: Varying the radius for "Near" definition

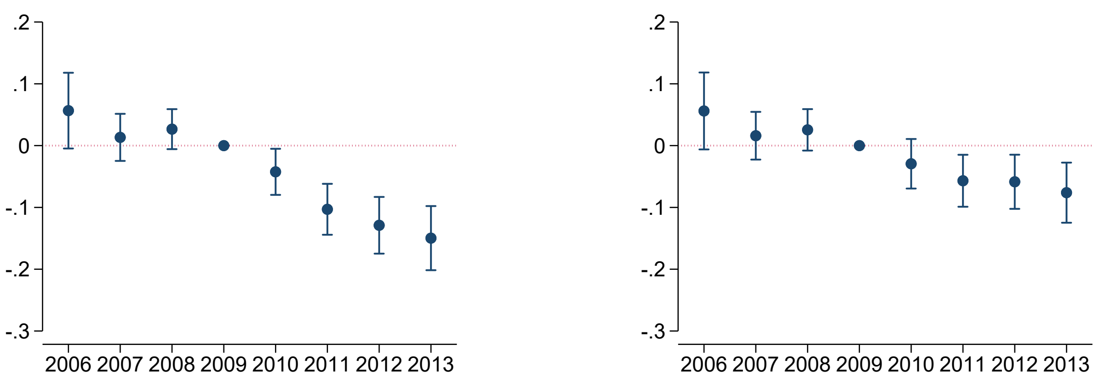


(a) Grade 3 (b) Grade 4

Point estimate and 95% confidence intervals for the β term in equation 1 plotted. Each point is the result of a separate estimation. The definition of the $Near_s$ variable was varied in each specification, taking the value of 1 for any school within 1-10 miles of the nearest battery recycling facility and zero for any schools farther away but in the same states as the ULAB recyclign facilities.

Figure A2: Effects of being close to a lead-acid battery recycling plant on scores, individual level results

Panel A: Math Scores Panel B: Spanish Scores



Note: Figure displays the coefficients and 95% confidence intervals from the individual-level event-study of being near a recycling plant when looking at math and Spanish scores as outcomes. Standard errors are clustered at the school level. The reference period is 2009 when the US changed its lead air quality standard.

Table A1: Number of students tested, by subject, grade, and year

Panel A: Primary school grades								
	Grade 3		Grade 4		Grade 5		Grade 6	
Year	Spanish	Math	Spanish	Math	Spanish	Math	Spanish	Math
2006	964,764	956,950	1,098,962	1,113,318	1,148,475	1,166,842	1,182,469	1,204,955
2007	1,414,599	1,414,372	1,457,865	1,457,725	1,608,936	1,608,879	1,674,748	1,674,707
2008	1,847,773	1,847,773	1,876,372	1,876,372	1,889,260	1,889,260	1,926,968	1,926,968
2009	1,889,749	1,889,749	1,798,896	1,798,896	1,766,137	1,766,137	1,769,359	1,769,359
2010	2,023,136	2,023,136	1,977,838	1,977,838	1,873,472	1,873,472	1,863,794	1,863,794
2011	2,096,655	2,096,655	2,068,812	2,068,812	2,007,179	2,007,179	1,894,190	1,894,190
2012	1,871,962	1,871,962	1,997,152	1,997,152	1,958,716	1,958,716	1,902,874	1,902,874
2013	1,939,129	1,939,129	1,980,548	1,980,548	2,090,967	2,090,967	2,069,033	2,069,033
Panel B: Lower and upper secondary school grades								
	Grade 7		Grade 8		Grade 9		Grade 12	
Year	Spanish	Math	Spanish	Math	Spanish	Math	Spanish	Math
2006					900,177	898,645		
2007					1,393,534	1,393,433		
2008					1,583,080	1,583,080	616,711	616,711
2009	1,665,348	1,665,348	1,657,853	1,657,853	1,552,949	1,552,949	655,276	655,276
2010	1,697,046	1,697,046	1,708,842	1,708,842	1,613,114	1,613,114	752,686	752,686
2011	1,758,378	1,758,378	1,685,339	1,685,339	1,612,146	1,612,146	698,118	698,118
2012	1,741,882	1,741,882	1,661,375	1,661,375	1,546,018	1,546,018	841,210	841,210
2013	1,919,870	1,919,870	1,733,528	1,733,528	1,633,943	1,633,943	973,871	973,871

Note: Each cell reports the number of students tested as part of ENLACE in a given grade, subject, and year. Tests for grades 7 and 8 did not start until 2009 and testing in grade 12 did not start until 2008.

Table A2: Effect of attending school close to a battery recycling facility, defining exposure using prevailing wind direction

	(1)	(2)	(3)	(4)
	30°downwind cone		90°downwind cone	
Panel A: Math scores				
Near & downwind of	-0.0794	-0.0848	-0.106***	-0.0868***
facility X Post 2009	(0.0588)	(0.0612)	(0.0290)	(0.0293)
Number of students		-0.000896***		-0.000895***
		(0.0000655)		(0.0000655)
Observations	1,141,093	1,141,093	1,141,093	1,141,093
R^2	0.516	0.526	0.516	0.526
Num. of clusters	48,830	48,830	48,830	48,830
Panel B: Spanish scores				
Near & downwind of	-0.0512	-0.0611	-0.0975***	-0.0878***
facility X Post 2009	(0.0562)	(0.0565)	(0.0284)	(0.0276)
Number of students		-0.000415***		-0.000414***
		(0.0000599)		(0.0000599)
Observations	1,141,007	1,141,007	1,141,007	1,141,007
R^2	0.560	0.567	0.560	0.567
Num. of clusters	48,829	48,829	48,829	48,829
Fixed effects:				
School-session-grade	✓	✓	✓	✓
Year	✓	✓	✓	✓
Grade-by-year		✓		✓
Session-by-year		✓		✓
State-by-year		✓		✓
Plant-by-year		✓		✓

Note: The unit of observation is school-session-grade-year. "Near & downwind of a facility" is a dummy variable that equals one if school s is located within two miles from the nearest lead-recycling plant $p(s)$ *and* downwind of that facility, and zero if the school s is farther away from it or not downwind. The $Post_t$ indicator takes the value 1 in 2009 and thereafter. The sample includes all school-sessions in grades 3, 4, 5, 6, and 9 which we observe at least once in the pre-2009 and at least once in the post-2009 period. Outcomes are school-session-grade means of students' standardized test scores, standardized at the grade-year level. Panel A reports estimates with math scores as the outcome; Panel B reports estimates with Spanish test scores as the outcome. In each column the two specifications, with math and Spanish as outcomes, include the same levels of fixed effects; only the outcomes are changed. Columns 1 and 2 define downwind using a 30 °cone and columns 3 and 4 use a 90°cone. Standard errors, in parentheses, are clustered at the school level. * p<0.1, ** p<0.05, *** p<0.01.

Table A3: Effect of attending school close to a battery recycling facility on proficiency levels

	(1)	(2)	(3)	(4)	(5)
Panel A: Math scores					
Near facility X Post 2009	-0.0250***	-0.0240***	-0.0261***	-0.0215***	-0.0200***
	(0.00538)	(0.00533)	(0.00539)	(0.00544)	(0.00547)
Number of students					-0.000311***
					(0.0000285)
Observations	1,141,093	1,141,093	1,141,093	1,141,093	1,141,093
R^2	0.501	0.503	0.508	0.509	0.509
Num. of clusters	48,830	48,830	48,830	48,830	48,830
Panel B: Spanish scores					
Near facility X Post 2009	-0.0205***	-0.0195***	-0.0224***	-0.0208***	-0.0203***
	(0.00546)	(0.00528)	(0.00531)	(0.00529)	(0.00530)
Number of students					-0.0000989***
					(0.0000250)
Observations	1,141,093	1,141,093	1,141,093	1,141,093	1,141,093
R^2	0.528	0.536	0.539	0.540	0.540
Num. of clusters	48,830	48,830	48,830	48,830	48,830
Fixed effects:					
School-session-grade	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓
Grade-by-year		✓	✓	✓	✓
Session-by-year		✓	✓	✓	✓
State-by-year			✓	✓	✓
Plant-by-year				✓	✓

Note: The unit of observation is school-session-grade-year. Near is a dummy variable that equals one if school s is located within two miles from the nearest lead-recycling plant $p(s)$, and zero if the school s is farther away from it. The $Post_t$ indicator takes the value 1 in 2009 and thereafter. The sample includes all school-sessions in grades 3, 4, 5, 6, and 9 which we observe at least once in the pre-2009 and at least once in the post-2009 period. Outcomes are the share of students in a school-session-grade that are considered proficient (score a proficiency level of 3 or 4) in a given subject. Panel A reports estimates with math proficiency as the outcome; Panel B reports estimates with Spanish proficiency as the outcome. In each column the two specifications, with math and Spanish as outcomes, include the same levels of fixed effects; only the outcomes are changed. Standard errors, in parentheses, are clustered at the school level. * p<0.1, ** p<0.05, *** p<0.01.