The Effects of Local Industrial Pollution on Students and Schools

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ABSTRACT

Using detailed education data for 1996–2012 from the state of Florida, we examine whether pollution from local Toxic Release Inventory (TRI) sites affects student achievement and high-stakes accountability school rankings. Using event study and difference-in-differences designs, we compare students attending schools within one mile of a TRI site that opens or closes to students attending schools between one and two miles away. We find that being exposed to air pollution is associated with 0.024 of standard deviation lower test scores, increased likelihood of suspension from school, and increased likelihood that a school's overall high-stakes accountability ranking will drop.

I. Introduction

Although industrial plants exist in every major city of the United States and release billions of pounds of toxic substances annually, there is little evidence about whether these pollutants harm child health and cognitive development. In 2014, Toxic

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Release Inventory (TRI) sites alone (which represent only one type of industrial plant) released 3.95 billion pounds of (untreated) toxic chemicals in America into the air, land, and water, out of 25.45 billion total pounds of toxic chemicals created in production-related wastes. Tens of thousands of known toxic chemicals are used by industries and businesses in the United States to make common products, such as pharmaceuticals, furniture, and automobiles. While most toxic chemicals are managed so that they are not released into the environment, some release of these chemicals is the inevitable byproduct of manufacturing. There are currently about 21,800 TRI sites operating across the United States, and the Environmental Protection Agency estimates that 59 million people (about 19 percent of the population) live within one mile of a TRI site (U.S. Environmental Protection Agency 2014). Furthermore, nearly 22 percent of all public schools were within one mile of a TRI facility in 2016.[1] Almost two-thirds of the population of the United States lives within three miles of a TRI facility.

Unlike criteria air pollutants (for example, particulate matter), which have been regulated for decades, little is known about the effects of most of the chemicals released by TRI facilities because most of the chemicals emitted have never undergone any kind of toxicity testing (U.S. Department of Health and Human Services 2010) and were essentially unregulated until 2011.[2] These regulations might now be rolled back.[3] Nevertheless, some studies have suggested that many airborne toxic pollutants could harm birth outcomes (Currie, Davis, Greenstone, and Walker 2015), cause cancer, and harm the brain and reproductive systems (Centers for Disease Control and Prevention 2009).[4]

Most studies to date have focused on the effects of pollution on birth outcomes. Though some research (Almond, Edlund, and Palme 2009; Bharadwaj et al. 2017; Black et al. 2019; Grönqvist, Nilsson, and Robling 2017; Persico, Figlio, and Roth 2019; Sanders 2012) has focused on the negative effects of exposure to pollution during gestation or early life on later human capital outcomes, less attention has been given to the effects of exposure to pollution during childhood. For example, less is known about the medium-term effects of pollution exposure in childhood (over several years) or how exposure to pollutants in the schooling environment affects children's performance in school. There are also very few studies of indoor air pollution, though we spend most of our lives indoors.

Acute, short-term exposure to pollutants might negatively affect children's cognitive and behavioral outcomes as well, though the evidence on this is limited. Marcotte (2017) compares children who take tests on days with different air quality and finds that high levels of pollen or fine airborne particulate matter lower test scores. Roth (2016) finds that pollution levels on testing days affect college students' performance on tests in the United Kingdom. Ebenstein, Lavy, and Roth (2016) also find that variation in pollution levels in Israel affects performance on high school exit exams. However, none of this

1. We made this calculation based on linking national-level NCES data to national-level TRI data.
2. The first time the U.S. government enforced limits on mercury and other toxic chemicals was in December 2011 with the Mercury and Air Toxic Standards (MATS) (Currie et al. 2015).
3. The Supreme Court of the United States decided against the MATS rule in 2015 for lack of sufficient cost–benefit analysis. The Trump administration is currently reviewing the rule to determine whether it will be repealed.
4. Most of the evidence we have on the neurotoxic effects of these pollutants is from studies using animal models.

evidence explores the effects of typically occurring amounts of pollution on school-age children or whether there might be cumulative effects over time.

In this study, we examine how both acute and cumulative exposure to air pollution affects a variety of child cognitive (standardized test scores and grade repetition), behavioral (suspensions from school), and health (attendance and asthma-related) outcomes. We also investigate how exposure to pollution from TRI sites impacts schools' success at meeting high-stakes accountability benchmarks under a high-stakes school accountability system. This is the first study to examine how the locations of schools themselves, even within a zip code, affect the cognitive development and human capital formation of the children inside[5] and to look at how the environmental quality of school settings affects schools' success at meeting high-stakes accountability benchmarks. In addition, this is the first study to examine the cumulative effects of air pollution over time on student test scores and to investigate the timing of exposure during middle childhood versus adolescence.

Using detailed annual education data from the entire state of Florida between 1996 and 2012, we identify the effects of pollutants on a variety of cognitive and behavioral outcomes using evidence from event study and difference-in-differences designs that leverage TRI plant openings and closings. We compare students attending schools within one mile of a TRI site that opens (or closes) to their previous outcomes before a site opening (or after a closing). The comparison group is composed of students attending schools between one and two miles away from a TRI site at the same time in the same zip code. By exploiting the short distance over which TRI toxicants can travel through air (that is, one mile) and the sudden rise in air pollution after a TRI site opening, we are able to isolate the effects of pollution from other difficult-to-observe and possibly endogenous factors, such as local sorting, avoidance behavior, and time-invariant characteristics of students and schools that happen to be near a TRI site that could affect child outcomes.

We find that contemporaneous exposure to pollutants in schools has significant, negative impacts on test scores: a TRI site opening within one mile of a school is associated with approximately 2.4 percent of a standard deviation lower test scores for students in the school. We also find that pollution increases the likelihood a student will be suspended by 1.6 percentage points and the likelihood of being absent from school by 0.4 percentage points. These effects vary by age, with a stronger negative effect of TRI site openings on younger students' test scores, but we find little evidence that cumulative exposure over several years causes worse outcomes. Additionally, we find that a TRI site opening within one mile of a school is associated with lower performance on school accountability measures, equivalent to a 2.7 percentage point increase in the likelihood a school's ranking drops one or more levels.

These findings contribute to our understanding of when and where exposure to pollution can harm cognitive development. While previous literature has focused on exposure in utero or at birth effects on test scores, we demonstrate that there are still substantial short-term effects of proximity to pollution for children and adolescents. In addition, this work reveals how the locations of schools themselves affect both students

5. There have been studies based on non-U.S. samples that examine variation in air pollution on testing days. Ebenstein, Lavy, and Roth (2016) examine the effects of exposure to air pollutants on students in Israel during high-stakes standardized testing.

and schools. Finally, this is the first paper to examine the impact of local environmental pollution on school rankings under a high-stakes accountability regime.

The remainder of the paper is organized as follows. Section II describes previous research on the effects of pollution on cognitive development and academic performance. Section III describes our empirical strategy for estimating the effects of pollution on student's test scores. Section IV describes our data, provides descriptive statistics, and establishes the link between TRI site openings and pollution levels. Section V describes the results of our estimation and a series of robustness checks. Finally, in Section VI, we conclude.

II. Background

Research on the effect of pollution on children most commonly focuses on the link between exposure and health outcomes, such as mortality, birth weight, or the prevalence of respiratory diseases for children in highly polluted areas.[6] Although a growing literature connects pollution exposure during gestation to negative birth outcomes[7] and cognitive outcomes, there is far less evidence on whether exposure to pollution after gestation might be equally detrimental to cognitive outcomes. For example, Persico, Figlio, and Roth (2019) explore the effects of in utero exposure to pollution on health and cognitive outcomes later in life, finding that pollutant exposure is associated with worse infant health, lower test scores, and a higher likelihood of behavioral incidents or repeating a grade. Ferrie, Rolf, and Troesken (2012) find effects of early exposure to lead on later army intelligence test scores. Almond, Edlund, and Palme (2009) and Black et al. (2019) use quasi-experimental designs and Scandinavian data to study the effects of exposure to radiation from nuclear fallout during gestation. Sanders (2012) investigates the relationship between county-level measures air pollution during gestation in Texas and later test scores, finding that a standard deviation decrease in mean pollution level at birth is associated with 1.9 percent of a standard deviation increase in high school test scores. Bharadwaj et al. (2017) compare Chilean siblings' differential exposure to air pollution during gestation during a period of rapid economic development in Chile, making use of data from three air-quality monitors in Santiago to show that exposure to carbon monoxide during the third trimester is associated with a 3 to 4 percent of a standard deviation decline in test scores in fourth grade.

There are few postnatal studies of the effects of pollution on cognitive development. Aizer et al. (2018) investigate the effects of lead exposure in early childhood on children's test scores by exploiting Rhode Island's rules regarding residential lead abatement. Rau, Urzúa, and Reyes (2015) uses a difference-in-differences design to estimate the contemporaneous effects of school proximity to toxic chemical sites in Chile on student test scores and found that attending schools more than a mile from such sites

6. For an overview of how in utero and early life exposure to negative environmental factors, such as pollution, can impact later life outcomes, see Almond and Currie (2011).

7. A growing literature has shown that children exposed in utero to pollution have higher infant mortality (Currie and Neidell 2005), lower birth weight (Currie et al. 2015), and a higher incidence of congenital anomalies (Currie, Greenstone, and Moretti 2011). Also, a number of epidemiological studies have found significant relationships between air pollution and preterm birth (Butler and Behrman 2007).

increases test scores by 7 to 9 percent of a standard deviation. In addition, Grönqvist, Nilsson, and Robling (2017) exploit the phase-out of leaded gasoline in Sweden to show that early exposure to lead pollution affects school grade point averages, high school completion, crime, earnings, and noncognitive skills.

A more recent strand of research explores the role that day-to-day variation in pollution plays in explaining school absenteeism or test performance, usually by focusing on how contemporaneous exposure to pollution may exacerbate respiratory diseases such as asthma, causing students to perform worse on days with worse pollution (Marcotte 2017). However, the majority of work on acute exposure has focused on samples outside the United States, except for Marcotte (2017). In a study of high school students in Israel, Ebenstein, Lavy, and Roth (2016) found that an increase in the level of particulate matter 2.5 (PM2.5) on the day of an exam is associated with a decline in student performance. A similar research design in the United Kingdom also found that elevated exposure to air pollution (PM10) on the day of a test is associated with lower test scores (Roth 2016). In this study, we investigate both the effects of acute exposure on school-age children, as well as the cumulative effects of continuous exposure to industrial emissions.

Drawing on previously developed models of pollution, health, and human capital (Graff Zivin and Neidell 2013; Currie et al. 2014), we argue that there are two main mechanisms through which medium-term pollution exposure might affect academic achievement and human capital formation. First, exposure to pollution might cause students to get sick with a respiratory illness and miss school (Currie et al. 2009; Ransom and Pope 1992), which could negatively affect their test performance. For example, Jans, Johansson, and Nilsson (2018) find that worsening air quality due to inversion episodes causes an increase in respiratory illnesses among children. Simeonova et al. (2018) also show that the implementation of a congestion tax in Stockholm decreased the rate of acute asthma attacks among children.

Second, pollution might affect children's cognitive performance through affecting their brains as they learn the material or take the test. For example, several studies using experimental animals (for example, dogs and rats) have found that air pollution might cause damage to the brain by altering the blood–brain barrier, leading to glial cell death and degeneration of neurons in the cerebral cortex (Block and Calderón-Garcidueñas 2009; Calderón-Garcidueñas et al. 2002; 2008a). Calderón-Garcidueñas et al. (2008a, 2008b, 2015) compare a small sample of children and adolescents in an urban, highly polluted environment (Mexico City) to those in less polluted, but economically comparable cities on a set of clinical and neuroimaging measures. They find that children in polluted areas have higher accumulation of markers of neurodegenerative disease, more white matter lesions associated with cognitive dysfunction, and lower performance on a set of fluid and crystallized cognition tasks. These results are illustrative of a larger epidemiological literature that find associations between exposure to pollutants and cognitive damage for children, but do not address selection and therefore cannot disentangle the effects of pollution on brain development from other factors correlated with pollutant exposure, such as socioeconomic status.[8] While we cannot fully distinguish

8. For a comprehensive review of the epidemiological literature on pollutant exposure and cognitive development, see Block et al. (2012) and Calderón-Garcidueñas et al. (2016).

between these competing explanations, we investigate possible mechanisms through which pollution affects child health, including absences and hospital visits. We find little support for missing school as the reason test scores decline with pollution exposure.

Our study is also different from previous work on contemporaneous impacts of pollution in five important ways. First, the majority of studies that focus on exposure in schools use variation in pollution levels the day of an exam, whereas our study focuses on the medium term, but cumulative effects associated with continued exposure to pollution due to proximity to a TRI site. Second, a novel contribution of this work is showing that even a relatively modest and ordinary increase in pollution exposure that happens when factories open is harmful to nearby children. Third, while most other studies have focused on high school exit exams or test taking in college, we are able to examine the effects of exposure to air pollution in children at different ages, from middle childhood through adolescence, as well as to look at cumulative exposure during childhood. A fourth way our paper is unique is that we focus specifically on the effects of one type of widespread industrial pollution, TRI sites, which emit a wider range of chemicals than have been studied in previous work and might be more toxic than other types of air pollution. Understanding the effects of industrial sites in particular has important policy implications when considering regulatory policy for high pollution industries, as well as districts' decisions about school placement. Fifth, we use a sample of students in the United States, providing evidence of the effects of pollutants within the U.S. school system. Given that low-income and Black students are more likely to live near TRI sites and other sources of industrial pollution (Persico, Figlio, and Roth 2019; Clark, Millet, and Marshall 2017), our study could provide important insights into the mechanisms through which poverty produces negative cognitive and human capital outcomes over time.

Finally, unlike previous studies which focus only on the links between pollution and individual academic performance, our work connects the effects of pollutant exposure on individual student test scores to the school's overall performance on high-stakes accountability measures. The state of Florida implemented a school accountability program known as the A+ Plan for Education in 1999. Under this accountability scheme, students in Grades 3–10 take annual curriculum-based standardized tests, and a school's aggregate scores on these exams are used to assign letter grades (A, B, etc.) to the school that result in rewards or sanctions depending on the school's performance.[9] This plan was later adopted as the state accountability system under the No Child Left Behind Act in 2001, which compelled states to adopt school accountability systems based on annual student assessments.

By linking data on TRI site openings to school accountability grades, we show that schools within one mile of a TRI site that opens are more likely to have their school grades drop than comparison schools between one and two miles away in the same zip code. Because previous work (for example, Rouse et al. 2013) has shown that low performance on school accountability measures impact school's instructional strategies, our results suggest that exposure to pollutants in schools may result in community-wide

9. For example, low-performing schools who receive F or D are placed under state staff oversight, who put in place a school improvement plan, and students at chronically low-performing schools (that is, schools that receive a failing grade two years in a row) are given vouchers to allow them to transfer to a better-performing public school or a private school. For more detail on the sanctions and rewards associated with Florida's accountability scheme, see Rouse et al. (2013).

impacts on educational policy, beyond just the effects on individuals' cognitive development and academic performance. In addition, schools in Florida that underperform continue to face sanctions under this policy, meaning that the stakes remain high. If schools are not fully responsible for the performance of students on these exams, this raises important questions about the fairness of such policies.

III. Empirical Strategy

To evaluate the effects of exposure to pollutants within a school environment on children, we leverage TRI plant openings and closing in a difference-in-differences design. We compare children attending school within one mile of a TRI site that opens or closes to children between one and two miles away from the site, before versus after a site opens or closes. In our analyses, we concentrate on schools located within one mile of a TRI site because, as shown in Panel A of Figure 1, we find that TRI sites primarily affect air quality within one mile of a site. This finding is consistent with a literature that finds that most types of air pollution, including all airborne toxics, PM2.5, and ultrafine particulate matter, do not travel farther than a mile.[10] Thus, the treatment group is students who attend schools within one mile of a TRI site while it is operating (either after it opens or before it closes), and the comparison group is students between one and two miles away from the same TRI site in the same neighborhood.[11] We also show the results nonparametrically in Online Appendix Table A1 and using 0.5-mile distance bins in Figure 5, which we discuss in more depth in Section V, and the results fade out by one mile from a TRI site.

This strategy allows us to deal with the difficulty inherent in estimating the relationship between pollution and academic achievement: the endogeneity of exposure to a TRI site. Schools near a recently opened site might differ from schools farther from a TRI site due to factors other than the levels of pollutants in the environment because the schools children attend, and the pollution to which they are subsequently exposed, are not randomly assigned. For example, schools closer to sources of pollution might serve students who are more disadvantaged in general.

Thus, we make two main identifying assumptions. First, we assume that the only thing that changed in a neighborhood that could affect children's academic outcomes is a TRI site opening or closing (and the associated change in pollution). Our estimates would be biased if there are unobserved factors affecting the outcomes of students attending schools within one mile of a TRI site that are correlated with a TRI site opening or closing. For example, when a TRI site opens, more motivated students might move away from a school to escape the pollution. Furthermore, if students do not move away when a site opens, or students move into a school nearer to an open TRI site, this could also be a sign that those students are experiencing other negative shocks that are unrelated to the pollution. If there is substantial residential sorting around an opening or closing, another mechanism through which a TRI site opening might affect students is

10. See, for example, Currie et al. (2015) and Anderson (2020).

11. See Online Appendix Table A1 where we also estimated these results using a continuous measure of distance interacted with a dummy variable for whether the TRI site was operating, rather than a binary indicator for being within one mile of an operating site. The results are quite similar—being one mile farther away from an open site is associated with 0.016 of a standard deviation higher test scores (significant at the $p < 0.05$ level).

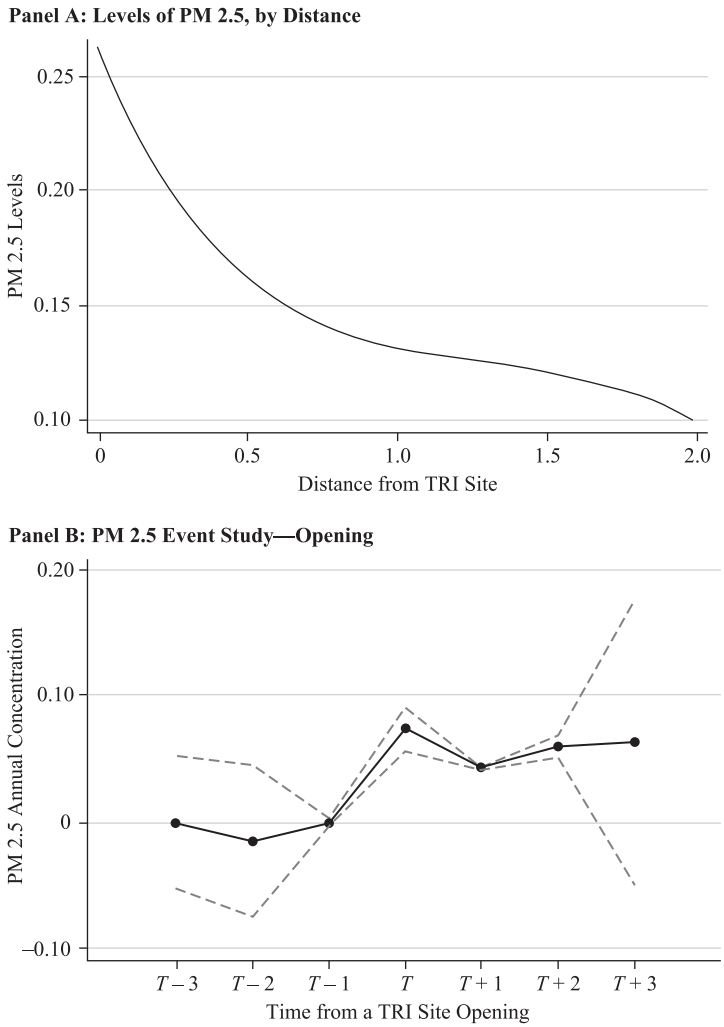

Figure 1

Particulate Matter (PM2.5) Levels over Distance Away from a TRI Site and after a TRI Site Opening

Notes: Panel A depicts the predicted level of fine particulate matter (PM2.5) conditional on distance from the TRI site. We predict pollution levels by calculating the distance between PM2.5 EPA monitors and the open TRI sites, regressing the average PM2.5 measured at a monitor on an indicator for whether the closest TRI is open, a quartic for distance from the open TRI site, and year fixed effects, and then using the predicted coefficients from this regression to pollution levels as a smooth function of distance. Panel B plots the coefficients from a regression of mean level of PM2.5 on leads and lags of a TRI site opening within a mile of the pollution monitor. T is the year the TRI site opens and all coefficients are normalized such that the coefficient in the year prior to opening ($T-1$) is zero. Dotted lines represent 0.95 confidence intervals for the coefficients. Standard errors are clustered at the pollution monitor level.

through peer effects. In addition, school quality might be affected if good teachers decide to leave the school because of the increase in pollution. On the other hand, a factory opening might both increase pollution and also stimulate the local economy (Greenstone, Hornbeck, and Moretti 2010), meaning that the positive impacts of better economic conditions might cancel out any negative impacts that could arise from pollution exposure.

The second assumption we make is that students attending schools one to two miles away from a TRI site can serve as a valid counterfactual over the same time period. In other words, we assume that in the absence of a TRI site opening or closing, students in schools within one mile of a TRI site would have followed the same trends in outcomes as students in the comparison group who attend schools one to two miles away. We present several pieces of evidence later in the paper to test these assumptions systematically and possible threats to validity.

In addition, our difference-in-differences model has several advantages that allow us to isolate the effects of exposure on test scores from other confounding factors by leveraging three features of TRI site exposure. First, we exploit variation in the timing of TRI sites opening and closing in Florida between 1999 and 2012. Because we observe some students before and after a TRI site opens and some before and after a TRI site closes, we can isolate the portion of student scores that are student- or school-specific and unrelated to exposure to the TRI sites. Second, our variation comes from the year a site opened or closed, the same year that students take the spring Florida Comprehensive Assessment Test (FCAT). Therefore, a site would have opened or closed relatively close to the exams (within a few months at most)[12] and likely before students were able to move away from the school due to the site opening.[13] Because neighborhoods that have multiple TRI sites might be different in unobserved ways from neighborhoods that have no TRI sites, we limit our main analysis to the effect of a single TRI site opening (where there were no TRI sites in the neighborhood prior to the opening) and the effect of a single TRI site closing. This also helps to allay concerns about residential or school mobility that may have happened when earlier sites opened.

Finally, we use the latitudes and longitudes of the schools and the TRI sites to calculate the distance between each public school in Florida and every TRI site in the state and designate a school as part of the treatment group if it is within one mile of the closest TRI site. Our control group is schools that are between one and two miles from the same TRI site. Since this distance difference is likely to capture only the different exposure level rather than any impacts the plant opening may have on the broader neighborhood, we can plausibly control for confounding factors, such as labor market improvements or changing housing markets. Empirically, this translates to the following model. A student i in school s, zip code z, and year t has some academic outcome Y_{iszt} that is modeled as follows:

$$(1)\quad Y_{iszt} = \beta_0 \mathbb{1}(\textit{Closest TRI Site within Mile})_s + \beta_1 \mathbb{1}(\textit{Closest TRI Site Open})_t + \beta_2 \mathbb{1}(\textit{Closest TRI Site within Mile}_s \times \textit{Closest TRI Site Open})_{st} + \beta_3 X_{it} + \beta_4 Z_{st} + \alpha_i + \gamma_z + \theta_t + \epsilon_{iszt}$$

12. If the TRI site opened after the students took the exams, this would bias our results toward zero.
13. Few students tend to move in the middle of the school year.

In our model, our treatment is being in a school within one mile of an open TRI site. The indicator $\mathbb{I}(\textit{Closest TRI Site within Mile})_s$ is equal to one if the student's school is within one mile of a TRI site and equal to zero if the school is between one and two miles of a TRI site. The indicator $\mathbb{I}(\textit{Closest TRI Site Open})_t$ is equal to one if in year t the closest TRI site to the school is open and equal to zero if in year t the site is closed. Our parameter of interest is therefore β_2, which represents the effect on test scores of a TRI site being open within a mile of a school. X_{it} is a vector of observable time-varying individual characteristics, including age, free or reduced-price lunch status, and whether or not the student switched schools that year. Z_{st} is a vector of observable time-varying school-level characteristics, including size, the school stability rate, the percent of teachers with an advanced degree, the percent of students who are Black, average maternal education by school, and the percent of married mothers by school. We also control for zip code–level fixed effects (γ_z), student fixed effects (α_i), and time fixed effects (θ_t). The addition of the year fixed effects allows us to account for trends over time throughout the period of our study. Including zip code fixed effects allows us to compare schools in the same neighborhood in Florida.[14] ϵ_{iszt} is the error term.

We use five different measures of student outcomes: standardized math and reading scores on the FCAT, the average of these two scores,[15] a binary indicator of behavioral incidents equal to one if the student had one or more behavioral incidents (for example, suspensions) in that year, and the rate of absences, calculated as the number of days absent divided by the number of days in the school year.

Because pollution affects test scores, and these scores are used to assign school grades in Florida, it stands to reason that pollution might translate to lower overall school performance on high-stakes testing measures. Since schools near TRI sites are slightly more disadvantaged (see Table 1), one might be concerned that the additional negative effects of TRI sites might contribute to disparities in school performance on high-stakes accountability measures. Under the accountability measures that schools face under No Child Left Behind and its successor Race to the Top, schools face great pressure to achieve high scores not only on standardized tests, but also on other measures of school accountability. For example, Florida's accountability scheme, the A+ Education Plan, creates sanctions for low-performing schools, such as vouchers that allow students to leave the district for better performing schools and public pressure from media and community groups. Under this plan, the Florida Department of Education assigns each school a yearly grade (A–F) on the basis of their performance on 11 school indicators.[16] These grades are reported in the Florida School Indicators Report (FSIR), allowing us to create a data set (Persico 2019) that includes school grade, location, and a set of the same school-level covariates drawn from FSIR in the individual level analysis. We assign each letter grade a numerical value, where A = 5, B = 4, C = 3, D = 2, and F = 1.

14. That is, rather than simply comparing all schools within one mile to all schools within one to two miles, we difference out the average achievement level in the zip code, making the comparison more plausibly schools near a site within a zip code to schools far from a site within a zip code.

15. The average was calculated as the mean of the math and reading score for students who had both test scores available. Students who had only one test score available were given an average equal to the available test score.

16. Schools receive grades based on performance on state standardized exams in English language arts (ELA), mathematics, science, and social studies, learning gains on each of those exams from the prior year, graduation rates from middle and high school, and enrollment rates in AP, IB, and other college accreditation courses.

Table 1
School and Neighborhood Characteristics within One and Two Miles of a TRI Site

	Treatment Group: Closest Site within a Mile		Control Group: Closest Site between One and Two Miles		
	Site Open	Site Closed	Site Open	Site Closed	Difference-in-Differences
Panel A: School-Level Characteristics					
Size	841.1	876.3	889.6	1,030	34.74
	(396.5)	(470.1)	(499.5)	(604.8)	[46.42]
Stability rate	0.935	0.933	0.935	0.941	0.003
	(0.032)	(0.033)	(0.029)	(0.030)	[0.002]
Percent of teachers with master's degree	0.301	0.318	0.315	0.331	–0.017
	(0.112)	(0.108)	(0.108)	(0.107)	[0.008]
Percent receiving free or reduced-price lunch	0.605	0.632	0.572	0.556	–0.018
	(0.489)	(0.482)	(0.495)	(0.497)	[0.018]
Percent Black	0.368	0.395	0.295	0.321	0.003
	(0.292)	(0.308)	(0.254)	(0.278)	[0.017]
Percent Hispanic	0.183	0.205	0.209	0.231	–0.006
	(0.227)	(0.239)	(0.243)	(0.253)	[0.009]
Average maternal education	12.09	12.03	12.19	12.38	0.076
	(1.128)	(1.066)	(0.948)	(1.046)	[0.081]
Percent mothers who are married	0.538	0.513	0.572	0.576	0.008
	(0.184)	(0.196)	(0.160)	(0.183)	[0.013]

(*continued*)

Table 1 (*continued*)

	Treatment Group: Closest Site within a Mile		Control Group: Closest Site between One and Two Miles		
	Site Open	Site Closed	Site Open	Site Closed	Difference-in-Differences
Panel B: Zip Code–Level Characteristics					
Percent white	0.661	0.634	0.717	0.700	–0.005
	(0.248)	(0.251)	(0.207)	(0.221)	[0.005]
Median household income	39,354.0	40,071.3	42,297.4	45,470.0	–53.94
	(10,254.6)	(12,572.6)	(11,801.3)	(14,778.0)	[313.1]
Median home value	137,428.6	145,785.9	146,012.9	165,918.1	618.6
	(62,653.3)	(66,142.2)	(59,796.9)	(77,692.3)	[1,421]

Notes: Column 1 statistics are for schools within a mile of a TRI site in years where the site is open. Column 2 shows statistics for schools within a mile of a TRI site in years where the site is not open. Column 3 shows statistics for schools between one and two miles of a TRI site in years where the site is open. Column 4 shows statistics for schools between one and two miles of a TRI site in years where the site is closed. Column 5 shows the differences-in-differences results of these four columns with time and zip code fixed effects. Standard errors are in brackets, and standard deviations are in parentheses.

Table 2
Difference-in-Differences Estimates for the Effect of a TRI Opening on Student Achievement and School Rankings

	FCAT Math (1)	FCAT Reading (2)	Average FCAT (3)	Behavioral Incidents (4)	Rate of Absences (5)	School Accountability Grade (6)	Probability School Grade Drops between the Year before and the Year after a TRI Opens (7)
Panel A: Full Sample							
TRI site is open within 1 mile (compared to schools 1–2 miles away)	–0.024	–0.025	–0.024	0.016	0.004		
	(0.008)	(0.006)	(0.006)	(0.009)	(0.001)		
Observations	777,973	777,864	778,517	953,305	921,862		
Panel B: Restricted to Stayers							
TRI site is open within 1 mile (compared to schools 1–2 miles away)	–0.029	–0.028	–0.029	0.016	0.003		
	(0.009)	(0.010)	(0.007)	(0.008)	(0.001)		
Observations	650,772	650,712	651,352	722,503	743,545		
Panel C: School-Level Difference-in-Differences							
TRI site is open within 1 mile (compared to schools 1–2 miles away)						–0.116	0.029
						(0.054)	(0.017)
Observations						1,150	1,183
Covariates	Y	Y	Y	Y	Y	Y	Y
Student FE	Y	Y	Y	Y	Y	N	N
Time FE	Y	Y	Y	Y	Y	Y	Y
Zip code FE	Y	Y	Y	Y	Y	Y	Y

Notes: Columns 1–5 present the results for different schooling outcome variables for students, and Columns 6-7 present the results for school-level high-stakes accountability outcomes. In all panels, the coefficient of interest is the effect of a single TRI site being open within a mile of the school. In Panel A, the sample includes our full sample of students. In Panel B, the sample is restricted to students who were in the school in the year prior to the year of observation (that is, "stayers"). All regressions in Panels A and B include student, year, and zip code fixed effects, as well as the age of the student, indicator for if receiving FRL, whether the student changed schools, average years maternal education, percent Black by school, percent of married mothers by school, school size, school stability rate, and percent of teachers with a master's degree by school. In Panel C, the regressions are at the school level and include all schools within two miles of a TRI site, controlling for zip code and year fixed effects, as well as percent FRL, school size, school stability rate, and percent of teachers with a master's degree by school. All standard errors are clustered at the school level and reported in parentheses.

Thus, we also estimate the effect of a TRI site operating on two school-level outcomes: the change in school's grade when a TRI site is operating and the likelihood a school's grade will drop following a TRI opening.

In our primary specification, we restrict our analysis to schools that have only one TRI site (or fewer) within a mile to ensure that treatment intensity is consistent across all schools in our sample. In reality, many schools in Florida have more than one TRI site within a mile, prompting a second analysis in which we estimate the effects of additional TRI sites on student outcomes, which we will discuss in the "Results" section. We identify the effects of pollution using two types of variation in exposure: changes in exposure due to openings or closings in TRI sites and changes in exposure due to students moving from schools that are not (are) within a mile of an open TRI site to schools which are (are not). The first form of variation is plausibly exogenous to unobservable characteristics of the student—decisions to open or close TRI sites in a given year are likely unrelated to the types of students we see in schools. As we discuss further below, an analysis of observable characteristics of schools and neighborhoods in our control and treatment groups before and after a site opens suggest that students within one mile of a TRI site have similar trends in observable traits to those between one and two miles from the site. This suggests that students in a school pre- and post-site opening differ only in terms of pollutant exposure.

However, our identification also partially comes from movement across schools, and one might be concerned that how students sort across schools is not exogenous. If students are switching schools in response to site openings or closings, this could mean that school quality lowers because of compositional differences in schools, rather than because of exposure to pollution. Additionally, if some of our identification comes from students who switch schools, we might be concerned that the estimates of the treatment effect are actually caused by the disruptive nature of moves, rather than pollution. To address these concerns, we control for changing schools and run a series of robustness checks (described in Section V.C) to ensure that our control and treatment group are comparable across time and show that movement across schools in response to TRI site openings is negligible.

We also restrict our main analyses in Panel B of Table 2 to students who did not change schools the year they experienced a change in exposure to a TRI site. By eliminating students who became treated by moving to a school with an open TRI nearby, we are able to test whether our effect sizes are driven by moves, rather than the change in pollution exposure. Our results are very similar using this sample. However, in the interest of understanding the average effects of a TRI site operating, we use the full sample of all students, with a control for whether the student changes schools in the year of the TRI opening (compared to the previous year) for all regressions and account for individual time-invariant characteristics by using student fixed effects.

IV. Description of the Data Sets

A. Florida Education and TRI Data

The sample in this study includes every child born in Florida from 1992–2002 and attending public school in the state of Florida in 1996–2012. There are 1,637,099 children who are observed in public schools in the state of Florida during this time. We

restrict our sample to students who attend a public school within two miles of a TRI site and students in Grade 3 or above (that is, students for whom we have FCAT scores), for a sample of 1,019,168 children. We observe each child for an average of 4.6 years, giving us approximately 4.6 million student–year observations. Of these children, about 624,574 children (that is, about 38 percent of all public-school children) attend school within one mile of a TRI site. As observed in Table 1, the 600 schools within one mile of a TRI site are similar on most of their demographic characteristics to those 604 schools between one and two miles of a TRI site.

We gathered data on the annual types of pollution released by TRI sites and the locations of TRI sites from the EPA. Because the toxic emissions measures in the TRI database have been widely criticized for containing substantial measurement errors,[17] we gathered data on the timing of TRI site opening and closings from the Florida Division of Corporations. The Division of Corporations hosts data on required annual tax report filings for companies who were operating in Florida each year, and we were able to match TRI sites based on business names and address information. In total, there are 1,670 TRI sites in Florida that are open at any point during our sample. Of those sites, 199 TRI sites releasing toxic chemicals were operating continuously within one mile of public schools between 1999 and 2012, 304 TRI sites releasing toxic chemicals began operating within one mile of public schools in Florida between 1999 and 2012, and an additional 378 TRI sites stopped operating between 1999 and 2012 within one mile of public schools in Florida.[18] More information on this data set is available in Online Appendix B.

As shown in Figure 2, TRI sites are located in most major cities in Florida, including often the most population-dense areas of these cities. About 30 percent of children in Florida live within one mile of a TRI site. Of schools for which we had latitudes and longitudes available, 30 percent of schools in Florida are located with one mile of the closest TRI site. A similar percentage of schools, 31 percent, are within one and two miles of the closest TRI site.

B. Comparisons of the Schools Less Than One Mile from TRI Sites to Schools between One and Two Miles from TRI Sites

Table 1 shows the attributes of the schools within one mile of a TRI site along a number of dimensions. Panel A lists characteristics of the school, including size, stability, percent of teachers with a graduate degree, and percent of students receiving free or reduced-priced lunch (FRL). Panel B lists zip code–level characteristics, including racial composition, income levels, and housing values. Means are presented separately

17. The data on emissions are self-reported and based on criteria that have varied over time. The EPA does not require plants to measure their emissions precisely, nor to report at all under certain circumstances. Facilities are required to report if they manufactured or processed more than 25,000 pounds of a listed chemical or "otherwise used" 10,000 pounds of a listed chemical. For persistent bio-accumulative toxins, the thresholds are lower. These thresholds have changed periodically over the life of the program. The EPA provides guidance about possible estimation methodologies, but plants estimate their emissions themselves. Estimating methodologies may vary among plants and over time (Currie et al. 2015).

18. Note that this is not the same as the number of schools that experienced an opening or a closing within a mile. Some TRI sites are within a mile of more than one school, and conversely, some schools are within a mile of more than one TRI site.

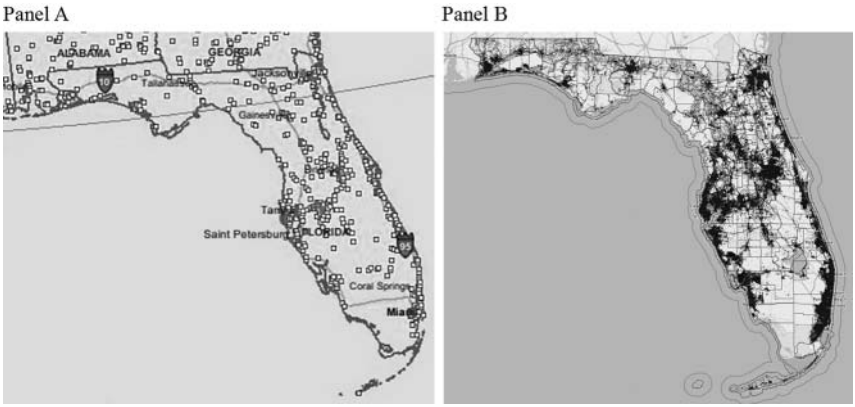

Figure 2

Locations of TRI Sites in Florida with Population Density Information

Notes: Panel A shows the location of TRI sites (white boxes) in the state of Florida in 2002 (according to the National Institute of Health's Toxmap website 2019). Panel B shows the population of Florida, where each dot represents 1,000 people, using data from the Census 2010 Summary File 1 to create the heat map in the U.S. Census Bureau mapping program CensusViewer. TRI sites are located in population-dense areas.

in Table 1 for the periods during which the closest TRI site is open versus closed and for those living within one mile versus within one to miles from the closest site. The sample of children attending public school within two miles of a TRI site is more disadvantaged than the average children in Florida. Schools within one mile from a TRI site are relatively less white, slightly more economically disadvantaged, and slightly smaller than schools between one and two miles. The last column, however, shows that schools in the treatment and control groups do not show significantly different trends in most characteristics when a TRI site is open versus closed.[19] The only category for which there is a significant difference in patterns for schools in the treatment group versus the control group is the percent of teachers with a graduate degree, which we control for in all specifications and discuss further in our discussion of mechanisms behind our results (Section V.D).

C. Variation in Pollution around TRI Sites

To confirm that site openings are in fact increasing exposure to toxicants, we do a preliminary exercise exploring the connection between level of pollutants in the air and site openings. First, we check our identifying assumption that schools further than one mile from the TRI site have low levels of pollution compared to closer schools. To do this, we calculate the distance between open TRI sites and EPA air monitors of the level of particulate matter 2.5 (PM2.5) and graph the level of PM2.5 over certain distances. As

19. This regression controls for zip code and year fixed effects, as well as age and an indicator for whether children changed schools.

Panel A of Figure 1 shows, we see a sharp decline as we get further from the TRI site, with PM2.5 amounts leveling out around the one-mile mark.

In addition to being interested in the distance over which openings increase emissions, we also check that the timing of pollutant increases matches with the timings of TRI sites going online. We run an event study, regressing pollutants levels reported by the monitors on indicators for year of opening and leads and lags on year of opening, as well as time fixed effects and pollution monitor fixed effects. The event study is a balanced panel restricted to openings within two miles of the monitor to mirror the sample we use in the main analysis of the paper. Standard errors are clustered at the EPA pollution monitor level, and all values are normalized with respect to pollution levels in the period prior to the opening (that is, the effects are normalized to be zero in period $T-1$, meaning that the levels in the graph show increases relative to period $T-1$). As Panel B of Figure 1 shows, there is a significant increase in levels of PM2.5 in the years following the opening, equal to about a 0.1 standard deviation increase in PM2.5 levels.

V. Results on Student Outcomes

A. Estimated Average Effects

Table 2 presents the results of our main difference-in-differences specifications, with Panel A showing the results for the effects of a single site operating for the full sample and Panel B showing the effects of a single site opening for a sample restricted to "stayers" (that is, students who were in the same school in the year prior). Each column in Columns 1–5 shows the effect for a different student outcome: FCAT math score, FCAT reading score, average FCAT score, likelihood student had at least one behavioral incident in the last year, and the rate of absences. We control for zip code, student and year fixed effects, as well as for student age, student FRL status, whether the student changed schools this year, average maternal education level at the school, percent of students who are Black, percent of mothers who are married, size of the school, stability rate, and percent of teachers with a graduate degree. The school-level results for the effect of a TRI site opening on school accountability grade level and the likelihood a school's grade will drop are presented in Panel C (Columns 6 and 7).[20] All standard errors are clustered at the school level.

We find substantial evidence to suggest that exposure to pollutants from TRI sites is associated with worse cognitive outcomes. As shown in Panel A, TRI site openings are associated with 2.4 percent of a standard deviation lower math FCAT test scores, 2.5 percent of a standard deviation lower reading FCAT test scores, and 2.4 percent of a standard deviation lower average FCAT test scores. In addition, a TRI site operating is associated with a 1.6 percentage point increase in the likelihood that a child will have a behavioral incident in school that year, though the effect is only significant at the $p < 0.1$

20. We control for zip code and year fixed effects, as well as average maternal education level at the school, percent of students who are Black, percent of mothers who are married, school size, school stability, the percent of teachers with a graduate degree, and the percent of students on free and reduced-price lunch in the specification in Panel C. Note that this regression does not use individual fixed effects, but rather is a difference-in-differences regression at the school level with zip code and year fixed effects and controlling for the same time-varying characteristics of schools as in Equation 1.

percent level. We find no effect of a TRI site opening on the likelihood of repeating a grade. Finally, we find that a TRI site operating increases the rate of absences from school in the year a TRI site is operating by 0.4 percentage points, suggesting that some children could be becoming sick and missing school. Given that the average rate of absences in Florida schools is 5.6 percent, this is a 7 percent increase in the rate of absences from school. Nevertheless, this amounts to about an additional 0.6 missed days on average, which is a relatively modest effect.[21]

For the sake of comparison, Marcotte (2017) finds that doubling test day PM2.5 exposure from an average day (25) to an unhealthy day (above 50) leads to a decrease in test scores of 2 percent, suggesting that a one standard deviation increase leads to a 0.8 percent decline. In a study of high school students in Israel, Ebenstein, Lavy, and Roth (2016) find that a one standard deviation increase in the level of particulate matter 2.5 (PM2.5) on the day of an exam is associated with a decline in student performance of 0.93 points, or 3.9 percent of a standard deviation. Because our estimates are based on a 0.1 of a standard deviation increase in pollution, this implies that a one standard deviation increase in pollution would decrease test scores by 24 percent of a standard deviation. Therefore, our impacts of prolonged exposure to a similar quantity of pollution would be roughly 6.2 times the size of those obtained by Ebenstein, Lavy, and Roth (2016) and 12 times the effect Marcotte (2017) finds.[22] Nevertheless, it is possible that the airborne toxics of TRI pollution (for instance, lead) in aggregate are worse than PM2.5 in other contexts. However, both these studies also use different samples, and differences in results could reflect different local average treatment effects.

The magnitude of the point estimates is similar for the sample restricted to children who do not change schools from the year before a TRI site opens (or closes) to the year the site opens (or closes) in Panel B of Table 2. Attending a school in which a TRI site is operating within one mile is associated with 2.9 percent of a standard deviation lower average test scores and a 1.6 percentage point increase in the likelihood of being suspended from school. However, the effect of pollution on being suspended from school is still only significant at the $p < 0.1$ level.

Panel C of Table 2 presents the results of the effects of a TRI opening on schools. We find that a school being within a mile of an open TRI site is associated with a significant decline in school grades, equivalent to 11.6 percent of a grade level. To make this statistic more easily interpretable, we can compare these results to another known contributor to lower school performance: the socioeconomic composition of the student body. For context, we find that a one percentage point increase in the number of FRL students is associated with a 1.04 percent of a grade level decline. Thus, we can think of

21. We also conducted a generalized method of moments (GMM) test of fixed versus random effects (which is similar to a Hausman test, but allows for clustered and robust standard errors) with standard errors clustered at the school level. The p-value of the statistic was less than 0.0000, which means that we can reject the null hypothesis that the random effects estimator is consistent. This provides evidence that our fixed effects model is preferred over random effects.

22. If the average standard deviation of the AQI for PM2.5 over the six semesters Marcotte uses is 9.84, and Marcotte is examining a 25 AQI point change, this is a 25/9.85 = 2.54 standard deviation change. He reports that this change results in 0.02 lower test scores. So a one standard deviation change would be 0.02/2.54 = 0.8 percent lower test scores overall, or 0.02 of a standard deviation lower scores on the day of the exam. This is 12 times smaller than our estimates, in which a one standard deviation change in pollution would result in 0.24 of a standard deviation lower test scores.

a TRI site opening as having a comparable effect to an increase in the proportion of disadvantaged students in a school by about 11 percentage points. We also find that TRI site openings are associated with a higher likelihood of the school falling at least one grade level in Florida's accountability ranking scheme (for example, from a B to a C). Schools within one mile of a TRI site opening have a 2.9 percentage point higher likelihood of having a lower school grade post-opening compared to schools between one and two miles of an opening (though this is only significant at the $p < 0.1$ level). For context, on average, 16 percent of schools in our sample experience a school grade decline per year.

An identifying assumption of these analyses is that time trends are similar for our control and our treatment group before the opening of a TRI site. If we instead had divergent time trends in test scores for students attending school further from the TRI sites, our estimates would be biased. Thus, we use an event study to explore whether the treatment and control group have similar time trends prior to a site opening and whether the effects of TRI site openings are persistent in the years following an opening. We estimate the following regression separately for the treatment group (children attending schools within a mile of a TRI site that opens) and the control group (children attending schools between one and two miles away from a TRI site):

$$(2) \quad Y_{ist} = \beta_0 + \sum_{j=-2}^{2} \beta_j \, \mathbb{1}[\tau_{it} = j]_{st} + \eta_i + \theta_t + \epsilon_{ist}$$

We include two years of leads and lags for the treatment, where τ_{it} denotes the year relative to the opening of a TRI site. For example, a value of $\tau_{it} = -1$ represents the students' FCAT scores one year before the year in which the TRI site opens (the reference year).[23] β is the effect of a site opening within one mile of a school on student test scores. η_i is a student fixed effect, which captures unobserved time-invariant characteristics of students,[24] and θ_t is a time fixed effect. We estimate this event study for children for whom there are five years of data, so that the event study is balanced, and exclude children who switched schools in the previous year to remove the potential endogeneity associated with school switching and isolate just the effect of a TRI site opening.[25]

Figure 3 shows the results of the event study on average test scores. While there are comparable trends in test scores in the years leading up to a TRI site opening for the treatment and control groups, there is a decline in test scores between the year before the TRI site opens (−1) and the year the TRI site opens (0), consistent with the effects being driven by the site opening rather than prior time trends. These negative effects persist and grow larger in magnitude in the two years after the year the site opens, which suggests that these effects persist and widen over time. In addition, the results in Year 0

23. Because this specification requires us to observe test scores for a student that does not switch schools for consecutive years, we are limited in the number of leads and lags we can include based on the data available. Unfortunately, restricting the sample to students for whom we observe more than five years of consecutive test scores and who attended school within one mile of a TRI site reduced the precision of our estimates substantially.

24. The year before a TRI site opens is the omitted category for both the treatment and the control groups.

25. We run this model for both the full sample and a sample where we exclude students who have switched schools. The results are not substantively different.

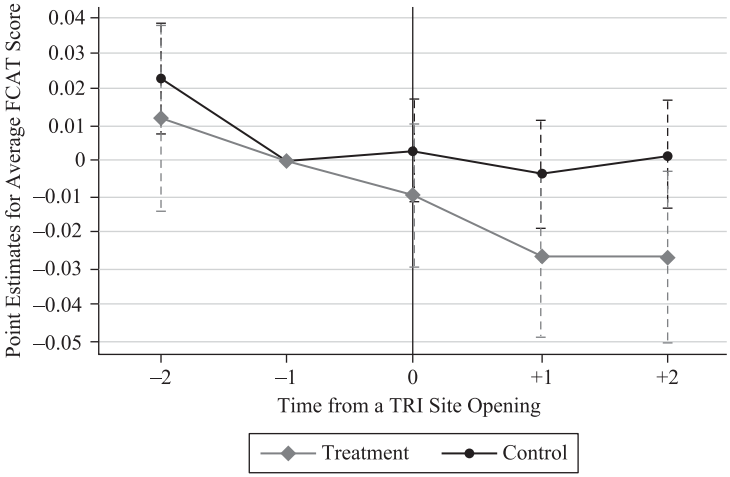

Figure 3

Event Study of the Effect of a TRI Opening on Students' Average Test Scores

Notes: This figure depicts an event study for the closest TRI site opening. The line with circle markers represents the coefficients from regressing average FCAT score on leads and lags of the year opening for the control group (students at schools between one and two miles from the closest TRI site). The line with diamond markers represents the same coefficients for the treatment sample or the students at schools less than a mile from the TRI site. A TRI site opens in Year 0. All coefficients are normalized to make the coefficient in year –1 zero for both samples. Dotted lines represent 0.95 confidence intervals. The regressions include student and time fixed effects, and all standard errors are clustered at the student level.

are primarily driven by TRI sites that open before students are tested in the spring. This implies that during the next year (1), all students would have been exposed to the TRI pollution, which is why the effect on test scores might increase in magnitude.

To test the cumulative effect of multiple TRI site openings, we next turn to a generalized difference-in-differences, in which we regress number of sites that are open within a mile of a student i's school in time t on their FCAT score, controlling for the same covariates in as in Equation 1, as well as student, time, and zip code fixed effects in both a linear and nonlinear specification. The maximum number of TRI sites ever open within a mile of a school is eight, and among schools that have at least one site open, the average number of sites open is 1.6 sites. One might expect that there would be a diminishing marginal effect of each additional TRI site, which would be consistent with lower average effects of each site in this specification compared to the model containing only the closest TRI site. To test this, we also run a nonparametric local linear regression in which we use polynomial basis functions up to the fourth power. These analyses show a large negative effect of the first site opening and smaller marginal declines due to additional sites. Figure 4 compares the added effect of each additional site on average FCAT scores in a linear model (Figure 4a) and a quartic model (Figure 4b). Unlike the linear model, which suggests a consistently increasing negative effect of site openings, the quartic model demonstrates that while the first site opening is associated with a 1.5 percent of a standard deviation lower average FCAT score, additional sites do

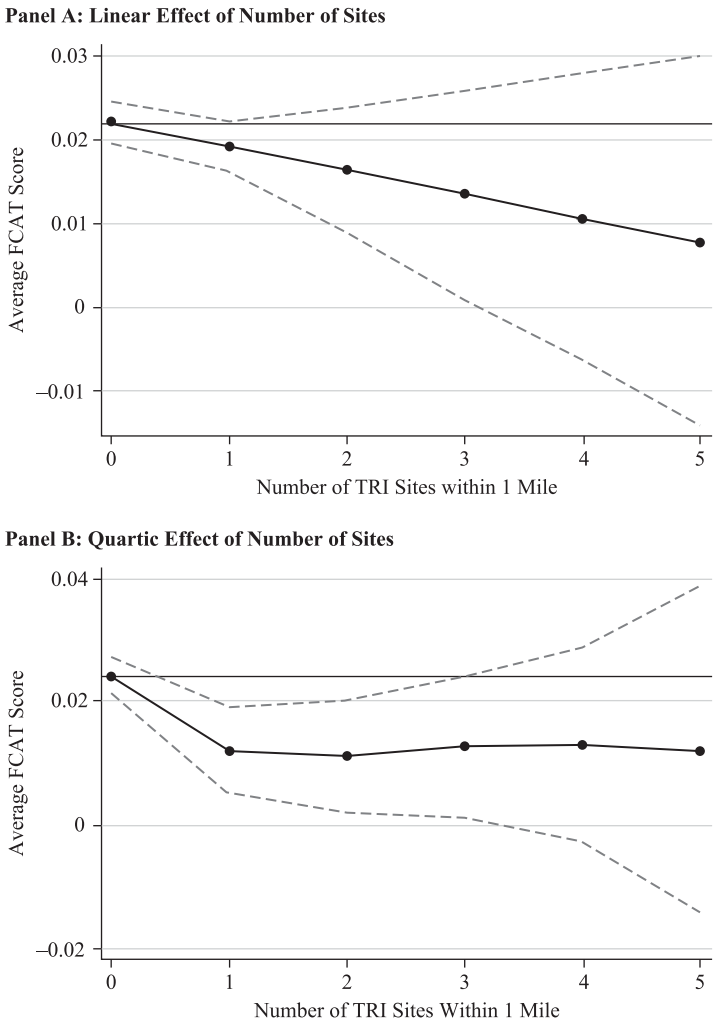

Figure 4

Linear and Quartic Effect of the Number of TRI Sites

Notes: This figure shows the cumulative predicted effect of each additional TRI site open within a mile of a student's school in a linear model (Panel A) and a quartic model (Panel B) regressing average FCAT score on number of open TRI sites within a mile, student, year, and zip code fixed effects, as well as the following covariates: age of the student, indicator for FRL, indicator for if student changed schools, percent of mothers with college degree at school, percent of mothers who are Black at school, percent of mothers who are married at school, size of school, stability rate of school, and percent of teachers with a graduate degree at school. Standard errors are clustered at the school level, and dashed lines represent 0.95 confidence intervals for the estimates.

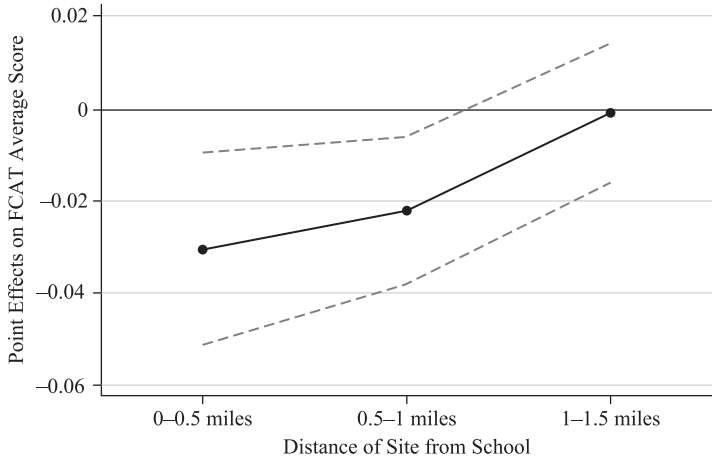

Figure 5

Fade Out of the Effects on Average Test Scores over Distance Away from a TRI Site

Notes: This figure shows how the effects of an opening fade out the further a TRI site is from a school. The dots represent the coefficients from a regression of student's average FCAT score on dummies for being in each distance bin of an open TRI site, also controlling for dummies for if the closest TRI is open, dummies for distance from the closest TRI site, student, year, and zip code fixed effects, as well as the following covariates: age of the student, indicator for FRL, indicator for if student changed schools, percent of mothers with college degree at school, percent of mothers who are Black at school, percent of mothers who are married at school, size of school, stability rate of school, and percent of teachers with a graduate degree at school. Standard errors are clustered at the student level, and dashed lines represent 0.95 confidence intervals for the estimates.

not significantly add to the effects, possibly because clean air laws constrain the amount of pollution that additional sites may release. Thus, for the remainder of the paper, we focus only on openings in settings with one TRI site, rather than multiple sites.

Our identification strategy relies on the theory that schools closer to a TRI site will have greater exposure to pollutants. Figure 5 presents the results disaggregated by distance from the TRI site, in which we interact an indicator for the site operating with distance bins (for example, site is open × <0.5 mile, site is open × 0.5–1 mile, etc.), with the students who are 1.5–2 miles from a TRI site as the control group. As expected, the strongest effects are on students who are closest to the TRI site, with students attending schools less than 0.5 miles and 0.5–1 miles from an open TRI site having, respectively, 2.8 percent and 2.0 percent of a standard deviation lower average FCAT scores than the control group. We also estimated these results (presented in Panel A of Online Appendix Table A1) using a continuous measure of distance interacted with a dummy variable for whether the TRI site was operating, rather than a binary indicator for being within one mile of an operating site. The results are quite similar – being one mile farther away from an open site is associated with 0.016 of a standard deviation higher test scores (significant at the $p < 0.05$ level). In addition, to ensure that the results were not driven by schools on the border of the one mile boundary when Figure 1 suggests that the

Table 3
Student Test Scores by Treatment Intensity (Emission Type and Wind Patterns)

	FCAT Math (1)	FCAT Reading (2)	Average FCAT (3)
Panel A: Wind Patterns			
Downwind >50% of the time	−0.035	−0.047	−0.040
	(0.022)	(0.012)	(0.016)
Observations	424,887	424,774	425,650
Panel B: Type of Emission			
Fugitive	−0.020	−0.019	−0.019
	(0.011)	(0.008)	(0.008)
Observations	622,756	622,661	623,308
Stack	−0.003	−0.012	−0.008
	(0.010)	(0.008)	(0.008)
Observations	614,898	614,806	615,468
Covariates	Y	Y	Y
Student FE	Y	Y	Y
Time FE	Y	Y	Y
Zip code FE	Y	Y	Y

Notes: This table depicts nine different regressions, each showing the effect of a TRI site opening on student test scores. Panel A runs our main specification by whether the school was downwind from the TRI site. Panel B runs our main specification separately for two methods of emissions: stack emissions and fugitive emissions. The dependent variables are standardized FCAT scores for math, reading, and the average of math and reading scores, respectively. All regressions include student, year, and zip code fixed effects, as well as the following covariates: age of the student, indicator if they changed schools, indicator for FRL, average maternal education by school, percent Black by school, percent of married mothers by school, size of school, stability rate of school, and percent of teachers with a master's degree by school. Standard errors are clustered at the school level and reported in parentheses.

pollution there would be lower, we experimented with using schools within 0.75 miles rather than within 1 mile, compared to schools 0.75 to 1 mile away in Panel B of Table A1, and the results are quite similar.

To investigate whether these results were predominantly driven by air pollution, we present results of a difference-in-differences specification in which we estimate the effects for children attending schools that are downwind from a TRI site within a mile of the school more than 50 percent of the time[26] (Table 3, Panel A). The comparison group is again children attending schools one to two miles away in the same

26. We use detailed wind data from the National Oceanic and Atmospheric Administration's Meteorological Assimilation Data Ingest System (MADIS) to estimate an average of annual wind direction as recorded by local wind monitors. We then calculated the bearing of the school from the TRI site using latitude and longitudinal coordinates and wind direction to determine whether the school was downwind of a TRI site more than 50 percent of the time annually. The methodology is similar to that of Heissel, Persico, and Simon (2019).

neighborhood. We find that the results are 63 percent larger in magnitude when we limit the sample to children who are downwind of a TRI site, suggesting that air pollution does drive the results.

In Panel B, we present the results of an exploratory analysis in which we estimate the effects of pollution on children for TRI sites that report emitting pollution through stacks, compared with TRI sites that have fugitive emissions. Because pollution released through smoke stacks is usually treated with scrubbers before being released, one would expect the results to be smaller in magnitude for stack releases than for fugitive releases. The results presented in Panel B of Table 3 confirm that, as expected, the effects on test scores are larger for fugitive releases than for stack releases.[27]

B. Heterogeneity of Estimated Effects: Age, Length of Exposure, Race, Economic Status, and Gender

Having population-level data from a state as large and diverse as Florida allows us to explore the effects of pollution across a variety of demographic groups. One reason it is important to explore the heterogeneity of the effects of pollution is that we can determine whether the results are stronger where we would expect them to be and observe the extent to which these results are driven by school locations. A large body of recent research suggests that children's cognitive development is more malleable at younger ages.[28] In addition, recent neuroscience research shows that the brain becomes more plastic and undergoes a second wave of synaptic pruning, neural development, and myelination during early adolescence in response to the hormones associated with puberty (Steinberg 2014; Reyna et al. 2012). This increased plasticity during early puberty could leave younger adolescents (ages 11–13) particularly vulnerable to environmental insults, and we might expect that earlier exposure to pollutants would have a greater negative impact on cognitive outcomes. First, we look at whether the effects of a TRI site opening differ across age groups. We reestimate our main specification separately by age. Table 4 shows these results for the sample split into age groups: Grade 3–7 (elementary/middle school) and Grades 8–12 (middle/high school).[29] There are clear age differences in the magnitude of the effects, with younger students experiencing

27. Because the EPA only includes data on stack versus fugitive releases for a subsample of TRI sites, the number of observations are smaller here than for the full sample. Sites with missing data on stack versus fugitive releases are treated as missing, though we know they released air pollution. The EPA defines fugitive emissions as unintended emissions from facilities or activities (for instance, construction) that "could not reasonably pass through a stack, chimney, vent, or other functionally equivalent opening" (see Title 40 of the Code of Federal Regulations, Sections 70.2 and 71.2). Thus, it might be the case that only the milder polluters volunteer this information. To investigate this, we ran an analysis estimating the effects of TRI sites that did not have information on stack or fugitive releases, and the point estimates on average test scores are slightly larger. This suggests that there could be some selection in the data in who reports these types of releases to the EPA, or for which types of TRI sites the EPA releases additional data.

28. There is increasing evidence that the developing brain is highly vulnerable to toxic exposures during the postnatal period (Bearer 1995; Grandjean and Landrigan 2014; Rice and Barone 2000). For example, exposure to lead at early ages lowers test scores (Aizer et al. 2018).

29. We chose this age cutoff for the age analysis to give us an even split in the number of grades included in the "young" and "old" groups. Though we tried other age specifications, splitting at the point when students switched schools (that is, Grades 3–5, 6–8, 9–12) resulted in nonsignificant results, partially due to smaller sample size and partially due to the loss in variation that we get from students moving from elementary to middle school or middle school to high school.

Table 4
Student Test Score Results by Time and Duration of Exposure

	FCAT Math (1)	FCAT Reading (2)	Average FCAT (3)
Panel A: Grade			
Grades 3–7 (elementary/middle school)	–0.031	–0.038	–0.034
	(0.009)	(0.006)	(0.007)
Observations	721,088	720,921	721,475
Grades 8–12 (middle school/high school)	–0.010	–0.001	–0.007
	(0.011)	(0.013)	(0.010)
Observations	292,469	292,449	293,180
Panel B: Cumulative Exposure			
1 or 2 years of exposure	–0.027	–0.024	–0.026
	(0.008)	(0.006)	(0.006)
Observations	663,246	663,147	663,746
3 or 4 years of exposure	–0.022	–0.025	–0.024
	(0.009)	(0.007)	(0.007)
Observations	599,755	599,675	600,163
5 or more years of exposure	–0.027	–0.026	–0.026
	(0.010)	(0.007)	(0.008)
Observations	577,806	577,736	578,198
Covariates	Y	Y	Y
Student FE	Y	Y	Y
Time FE	Y	Y	Y
Zip code FE	Y	Y	Y

Notes: This table reports regression coefficients that demonstrate heterogeneity by period of exposure. The coefficient of interest is the effect of a TRI site being open within a mile of the school. The dependent variable in are standardized FCAT scores for math, reading, and the average of math and reading scores, respectively. Panel A shows results for the sample split by grade level (Grades 3–7 and Grades 8–12). Panel B shows results for the sample split by the number of years the student was exposed to an open TRI site within a mile (1–2 years, 3–4 years, or 5 or more years). All regressions include student, year, and zip code fixed effects, as well as the following covariates: indicator for FRL, indicator for if student changed schools, average maternal education, percent of mothers who are Black at school, percent of mothers who are married at school, size of school, stability rate of school, and percent of teachers with a graduate degree at school. Standard errors are clustered at the school level and reported in parentheses.

declines in test scores that are four times as large in response to a TRI site opening. A TRI site opening is associated with a 0.034 of a standard deviation decline in average FCAT scores for elementary school students, compared to a 0.007 of a standard deviation decline in average FCAT scores for high school students.

Next, we examine the results by length of exposure. Panel B of Table 4 presents the results of an analysis of years of exposure to the TRI pollution. Generally, children

exposed to more years of TRI pollution do not have worse test scores. Children exposed to five or more years of TRI pollution have 0.026 of a standard deviation lower test scores, compared to children exposed to one or two years of TRI pollution whose test scores are also 0.026 of a standard deviation lower than unexposed children. Children exposed for between three and four years also show similar results to children exposed for only one or two years, implying that much of the effect of pollution exposure happens in the first two years of exposure. One explanation for this pattern of results is that the effects of TRI pollution exposure may persist beyond the period of direct exposure. This would be the case if exposure to pollution in earlier grades has persistent effects on either cognition, health, or skill acquisition that last even after students stop being exposed to pollution. Heissel, Persico, and Simon (2019) also find that children who move from a school downwind of a highway to one that is upwind do not see test score gains after moving to a less polluted school. Nevertheless, it is difficult to determine the extent to which cumulative pollution exposure might matter given that this intersects with age of exposure and treatment intensity.

We reestimate our main specification by race for non-Hispanic white, non-Hispanic Black, and Hispanic students (Table 5, Panel A) and by economic status (Table 5, Panel B) for students always receiving free or reduced-price lunch (FRL) in our sample, students sometimes receiving FRL, and students who never received FRL. The effects of TRI site exposure on test scores are quite similar for white, Black, and Hispanic students. A TRI site opening is associated with a 2.9 percent of a standard deviation decline in average FCAT scores for Black students, compared to a 2.3 percent of a standard deviation decline for white students. The slightly stronger coefficient for Black students might be because Black children are more likely to live closer to TRI sites, meaning that they might be getting exposed to pollution both at home and at school. Several studies have found that Black children are more likely to live nearer to sources of pollution in general (Anderton, Oakes, and Egan 1997; Chakraborty and Zandbergen 2007; Persico, Figlio, and Roth 2019) and TRI pollution in particular (Perlin, Sexton, and Wong 1999; Perlin, Wong, and Sexton 2001).[30] As seen in Table 1, Black students are also slightly overrepresented in schools within one mile of a TRI site. On the other hand, it might also be the case that parental compensatory behavior or avoidance behavior could vary by race and socioeconomic status. While the point estimates were larger in magnitude for Black students, the differences between students of different races are not statistically significant at the $p < 0.10$ percent level.[31]

We also do not see a statistically significant difference in exposure to TRI pollution across socioeconomic categories: a TRI opening is associated with similarly lower test scores for all students. Finally, we test whether our effects differ by gender and find that TRI site openings are associated with lower test scores for both male and female students in Panel C of Table 5, and the results do not differ significantly across gender. Thus, the general pattern of results holds across race, socioeconomic status, and gender. Taken

30. Unfortunately, for the purposes of this study we do not have home address data for the time children are in school, so we are unable to test whether this is the case.

31. In this regression, we interacted a dummy variable for each race with the dummy for treatment. We did the same for students in different FRL categories and gender. None of the results within a regression (for example, race) were significantly different from each other at the $p < 0.1$ level.

Table 5
Student Test Score Results by Race, Economic Status, and Gender

	FCAT Math (1)	FCAT Reading (2)	Average FCAT (3)
Panel A: Race			
White	–0.021	–0.024	–0.023
	(0.008)	(0.006)	(0.006)
Black	–0.032	–0.025	–0.029
	(0.008)	(0.006)	(0.006)
Hispanic	–0.010	–0.023	–0.017
	(0.008)	(0.007)	(0.007)
Observations	777,973	777,864	778,517
Panel B: Economic Status			
Always FRL	–0.026	–0.023	–0.024
	(0.007)	(0.006)	(0.005)
Sometimes FRL	–0.025	–0.026	–0.025
	(0.005)	(0.005)	(0.005)
Never FRL	–0.019	–0.027	–0.023
	(0.008)	(0.006)	(0.006)
Observations	777,973	777,864	778,517
Panel C: Gender			
Female students	–0.022	–0.024	–0.023
	(0.005)	(0.003)	(0.003)
Male students	–0.026	–0.026	–0.026
	(0.008)	(0.006)	(0.006)
Observations	777,973	777,864	778,517
Covariates	Y	Y	Y
Student FE	Y	Y	Y
Time FE	Y	Y	Y
Zip code FE	Y	Y	Y

Notes: Panel A runs our main specification interacted by race: white, Black, and Hispanic. Panel B runs our main specification by economic status, where a student is always FRL if they reported receiving free or reduced-price lunch in every period we observe them, sometimes FRL if they sometimes receive FRL, and never FRL if they never receive FRL. Panel C runs our main specification by gender. The dependent variables are standardized FCAT. All regressions include student, year, and zip code fixed effects, as well as the following covariates: age of the student, indicator if they changed schools, indicator for FRL (for race specification), average maternal education by school, percent Black by school, percent of mothers who are married at school, size of school, stability rate of school, and percent of teachers with a graduate degree at school. Standard errors are clustered at the school level and reported in parentheses.

together, these findings suggest that there may be little avoidance behavior in this particular setting, since students who are attending school together may all be exposed to the same pollution during school hours.

C. Additional Threats to Internal Validity

To test the robustness of our results, we run a series of analyses to address the possibility of bias due to student sorting across districts, different time trends for the treatment and control groups, or serial correlation in our outcome variable. First, to test whether our findings are biased by student sorting across locations in response to TRI site openings, we compare movers and stayers after openings and closings to movers and stayers following years where there was no change in TRI status to see if movers are different in terms of observable characteristics in the year of a TRI site opening/closing (compared to the year before an opening). As shown in Table 6, while movers tend to be more economically disadvantaged and lower scoring on both math and reading tests than stayers, the movers are not significantly different in years following an opening versus years in which there was no change in the number of TRI sites emitting pollutants nearby. Additionally, the majority of moves across schools occur as students transition from elementary to middle school or middle to high school, meaning that these are transitions happening for all students in the district and less likely to be disruptive moves than moves across districts. This suggests that since we do not see sorting on observables in response to a site opening, it is possible that moves are plausibly exogenous to TRI site status. We also estimate the results using students who were in the same school the year prior to the year of interest (that is, the change in exposure to pollution is not due to them moving into or away from a school near a TRI site), and the results are very similar in this specification, presented in Panel B of Table 2.[32]

Table 7 presents the results of several more robustness checks. In Panel B, we show the results for our baseline specification without any time-varying demographic or school-level controls. The point estimates are somewhat larger in magnitude, suggesting that variations in school quality might account for some, but not all, of the effect of a TRI opening on children's test scores. Next, we test the robustness of our estimates to differing time trends by adding separate time trends for the treatment and the control group. The magnitude of our estimate of the coefficient on TRI site openings drops only slightly, moving from a 2.4 percent of a standard deviation decline in average FCAT test scores in our main specification (Table 7, Panel A) to a 2.3 percent of a standard deviation decline in average FCAT test scores once we control for treatment-specific time trends (Table 7, Panel C).

We also might be concerned about serial correlation in student test scores. Bertrand, Duflo, and Mullainathan (2004) show that many difference-in-differences applications suffer from issues of serial correlation in the dependent variable, resulting in incorrect estimates of standard errors. Using randomly assigned treatments of placebo policies across states, they showed that random interventions are found significant 45 percent of the time at the $p < 0.05$ level. To address this concern, we run a robustness check in

32. We also estimate the effects just for those who encounter TRI pollution by switching schools. While the results for children who move are very similar to those who stay, they are slightly smaller in magnitude, which would be expected if some fraction of students change schools before a TRI site opens or are only attending school near a TRI site for part of the year.

Table 6
Descriptive Statistics on Students Who Move Following TRI Openings, Closings, and Neither

	Panels A1 and A2: TRI Site Opens in Year T			
	Panel A1: Doesn't Move in Year $T+1$		Panel A2: Moves in Year $T+1$	
	Mean in Year $T-1$ (1)	Mean in Year T (2)	Mean in Year $T-1$ (3)	Mean in Year T (4)
Percent ELL	0.184	0.176	0.197	0.190
	[0.388]	[0.381]	[0.397]	[0.392]
Percent disabled	0.252	0.253	0.269	0.271
	[0.434]	[0.435]	[0.444]	[0.444]
Standardized FCAT, math	0.074	0.082	0.011	–0.051
	[0.944]	[0.926]	[0.953]	[0.953]
Standardized FCAT, reading	0.082	0.102	0.020	–0.047
	[0.938]	[0.919]	[0.949]	[0.966]
Percent FRL	0.557	0.548	0.608	0.603
	[0.497]	[0.498]	[0.488]	[0.489]

(*continued*)

Table 6 (*continued*)

	Panels B1 and B2: TRI Site Neither Opens nor Closes in Year T			
	Panel B1: Doesn't Move in Year $T+1$		Panel B2: Moves in Year $T+1$	
	Mean in Year $T-1$	Mean in Year T	Mean in Year $T-1$	Mean in Year T
Percent ELL	0.186	0.181	0.173	0.171
	[0.389]	[0.385]	[0.378]	[0.376]
Percent disabled	0.242	0.239	0.256	0.257
	[0.428]	[0.427]	[0.437]	[0.437]
Standardized FCAT, math	0.097	0.097	–0.004	–0.061
	[0.948]	[0.947]	[0.966]	[0.976]
Standardized FCAT, reading	0.094	0.102	–0.001	–0.059
	[0.940]	[0.937]	[0.958]	[0.973]
Percent FRL	0.574	0.570	0.628	0.624
	[0.495]	[0.495]	[0.483]	[0.484]

(*continued*)

Table 6 (*continued*)

	Panels C1 and C2: TRI Site Closes in Year T			
	Panel C1: Doesn't Move in Year $T+1$		Panel C2: Moves in Year $T+1$	
	Mean in Year $T-1$	Mean in Year T	Mean in Year $T-1$	Mean in Year T
Percent ELL	0.197	0.195	0.206	0.202
	[0.397]	[0.396]	[0.404]	[0.401]
Percent disabled	0.246	0.238	0.263	0.261
	[0.431]	[0.426]	[0.440]	[0.439]
Standardized FCAT, math	0.132	0.138	0.003	–0.039
	[0.956]	[0.938]	[0.965]	[0.964]
Standardized FCAT, reading	0.131	0.144	0.014	–0.032
	[0.948]	[0.930]	[0.954]	[0.966]
Percent FRL	0.556	0.553	0.629	0.618
	[0.497]	[0.497]	[0.483]	[0.486]

Notes: This table contains summary statistics in year prior to a TRI event ($T-1$) or the year of a TRI event (T) for students attending school within one mile of a TRI site who move or do not move in three types of TRI events. Each column–row cell presents the means for either the year before the TRI event ($T-1$) or the year of the event (T) with standard deviations below in brackets. Odd columns show the means in the year before an opening, closing, or neither, while even columns show the means for the year of the TRI event. Panel A1 shows the means for students who stay in the year before and the year of a TRI site opening nearby, while Panel A2 shows the means for the movers in the year before the opening and the year of the opening. Panel B1 shows students who stay where there is no change in status for a TRI site (for example, if there was no site open nearby in year $T-1$ or in year T), while Panel B2 shows the means for movers. Panel C1 shows students who stay in the year before or the year of a TRI site closing nearby, while Panel C2 shows the means for the movers over the same time window. Statistics shown include the percent of movers or stayers who were ELL students, the percent of movers/stayers who were designated as disabled, the percent of movers/ stayers who received free or reduced-price lunch, and the standardized FCAT scores in reading and math for movers or stayers in the year before and the year of the TRI event.

Table 7
Student Test Score Results without Controls, Controlling for Time Trends, and a Placebo Test

	FCAT Math (1)	FCAT Reading (2)	Average FCAT (3)
Panel A: Baseline Specification			
	–0.024	–0.025	–0.024
	(0.008)	(0.006)	(0.006)
Panel B: Baseline Specification without Controls			
	–0.035	–0.038	–0.037
	(0.008)	(0.006)	(0.007)
Panel C: With Group Time Trends			
	–0.020	–0.025	–0.023
	(0.008)	(0.006)	(0.006)
Panel D: Placebo Test Randomizing Treatment			
	–0.001	0.000	–0.000
	(0.001)	(0.001)	(0.001)
Student FE	Y	Y	Y
Time FE	Y	Y	Y
Zip Code FE	Y	Y	Y
Observations	708,716	708,605	709,117

Notes: This table depicts a robustness checks to our main specification (which is denoted Baseline in Panel A). Panel B shows the main effects from the same specification in Panel A, but without any time-varying school-level control variables included. Panel C shows the effect of TRI sites when group-specific time trends are included (that is, time trends for the control group of students between one and two miles of a site and time trends for the treatment group of students less than one mile from the site). Panel D shows results of a placebo treatment, where we randomly assign schools to be treated to check that there is no effect. The dependent variables are standardized FCAT scores for math, reading, and the average of math and reading scores, respectively. All regressions include student, year, and zip code fixed effects, as well as the following covariates: age of the student, indicator for FRL, average maternal education by school, percent of mothers who are Black at school, percent of mothers who are married at school, size of school, stability rate of school, and percent of teachers with a graduate degree at school. Standard errors are clustered at the school level and reported in parentheses.

which we rerun a difference-in-differences specification with a placebo treatment. We randomly assign each TRI site to be on or off in each year and then rerun our differences-in-differences regressions with the placebo treatment.[33] Ostensibly, we should not see a significant effect of this random treatment. As Panel D of Table 7 demonstrates, there

33. For each school, we draw a random value from a uniform distribution in each year. For values less than 0.5, we assigned the "placebo" treatment to be closed and for values greater then 0.5 we assigned the "placebo" treatment to be open.

is no significant effect of a placebo treatment on student test scores, suggesting our findings are robust to concerns about serial correlation.

D. Potential Mechanisms

Even if students are not differentially sorting into different schools in the year following a TRI site opening or closing, one might still be concerned that teachers could leave the schools within one mile of a TRI site after an opening. To test whether teacher sorting accounts for these findings, we estimate a set of school-level regressions with zip code and time fixed effects in Column 5 of Table 1, controlling only for students' ages and whether they switched schools. This allows us to determine whether a TRI site operating is associated with teachers moving across schools. Schools in the treatment and control groups do not show significantly different trends in most characteristics when a TRI site is open versus closed, except for the percentage of teachers with master's degrees.

To further test whether students who are exposed to TRI pollution are more likely to have differential exposure to schools of different quality or different types of peers, we also estimate our primary specification with student, zip code, and time fixed effects where the outcomes are characteristics at the school level (Table 8). The estimates depicted in Column 1 of Table 8 are similar to those in the last column of Table 1: children attending schools near operating TRI sites experience schools that for most characteristics follow similar trends to schools one to two miles away. There are no statistically significant changes in the percent of students who are Black or Hispanic, percent of mothers who are married, maternal education, or the percent of children who are English language learners between schools within one mile of an operating TRI site and schools one to two miles away. However, schools within one mile of an operating TRI site are associated with a 1.4 percentage point decrease in the percent of teachers with master's degrees,[34] compared to schools between one and two miles away. Nevertheless, there is no statistically significant change in teachers' average years of experience, and the point estimate is near zero. Furthermore, the literature on teacher education does not suggest that having a master's degree is associated with increased student achievement.

While school size does not change differentially between the treatment and control groups in Table 1, we also find that students attending schools near an operating TRI site attend schools that are about 73 students larger than students attending school farther away. In addition, the schools within a mile of an operating TRI site have a stability rate that is 0.4 percent higher than schools one to two miles away. We consider these to be relatively modest changes in school quality and control for the percent of teachers with a master's degree, school size, and school stability in all specifications, which suggests that this does not account for our findings.

Next we investigate whether children's health might be a mechanism through which air pollution affects these outcomes, since air pollution is known to compromise respiratory health through exacerbating asthma (Simeonova et al. 2018) and causing respiratory diseases (Beatty and Shimshack 2011; Jans, Johansson and Nilsson 2018).

34. Given that 31.8 percent of teachers within one mile of a TRI site have a master's degree, this amounts to a 4.4 percent decrease in the percent of teachers with master's degrees overall, which is a relatively modest change.

Table 8

Possible Mechanisms—Impact on Student and School Characteristics and Local Health of a TRI Site Operating within One Mile of a School

	Primary Specification	Zip Code–Level Results
	TRI Site Is Open within One Mile (Compared to Schools 1–2 Miles Away)	TRI Site Is Open
Percent Black	0.004 (0.005)	
Percent Hispanic	–0.001 (0.003)	
Maternal education	0.026 (0.021)	
Percent of married mothers	–0.001 (0.003)	
Individual FRL status	0.004 (0.003)	
Percent English language learner	–0.002 (0.003)	
Percent of teachers with master's	–0.014 (0.005)	
Teacher average years of experience	0.068 (0.158)	
School size	73.41 (34.92)	
Stability rate	0.004 (0.001)	
Percent of students Absent >21 days	0.016 (0.005)	
Number of hospitalizations for asthma by zip code		0.401 (1.561)
Number of emergency room visits for asthma by zip code		0.540 (0.435)
Observations	978,831	418

Notes: This table shows results from a set of balancing tests in which student and school characteristics are regressed on our treatment variable (attending school within one mile of an operating TRI site), with our primary specification: which includes student, year and zip code fixed effects, an indicator for changing schools, age, and FRL, and time-varying school-level controls. Each row represents the results of a separate regression. Standard errors, clustered on school, are below the point estimates in parentheses in Column 1. The last column shows results from a regression with zip code and year fixed effects controlling for percent white, percent Black, and median income by zip code. Standard errors are clustered at the zip code level.

This could cause poorer academic performance by making students miss school. Alternatively, another pathway through which pollution might affect test scores is by directly affecting cognitive skill formation. Thus, we also investigated whether absences from school could explain our findings by controlling for the student-level rate of absences as a "bad control." When we control for the rate of absences, the effect on average test scores of a TRI site operating is −0.022 of a standard deviation (and statistically significant at the $p < 0.01$ level), which is very similar to the estimates in Table 2 of −0.024. While we cannot fully distinguish between these competing explanations (since sick children might still attend school), this suggests that being absent from school does not drive the results on test scores. In addition to individual-level absence data, we use school-level data on the proportion of students who are absent from school more than 21 days and find that a TRI site operating within a mile of a school is associated with a significant 1.6 percentage point increase in the percentage of students who miss school for more than 21 days (compared to schools one to two miles away) in Column 1 of Table 8.[35] Given that the student-level data show a more modest increase in absences of only 0.4 percentage points, this suggests that students who are absent often are driving the results.

Using zip code–level data from Florida Environmental Public Health Tracking, we also investigate whether a TRI site opening caused increases in the number of asthma-related emergency room visits and hospitalizations.[36] We regress an indicator for whether a TRI site was open on the number of emergency room visits or hospitalizations, controlling for demographic characteristics of the neighborhood (that is, percent white, percent Black, and median income) and using zip code fixed effects. The results of this analysis, presented in Column 2 of Table 8, suggest that there is no significant increase in asthma-related hospitalizations or emergency room visits following a TRI site opening.

VI. Conclusion

This is the first large-scale study to investigate the short- and medium-term effects of exposure to pollution during childhood and to compare exposure to air pollution at different ages. Using difference-in-differences and event study designs, we find that acute exposure to pollution decreases test scores by between 2 and 4 percent of a standard deviation. We also find that exposure to pollution in middle childhood has much larger effects on test scores than exposure during later adolescence. Nevertheless, exposure to air pollution at any time still has negative consequences on test scores, and there is suggestive evidence that it affects the likelihood of getting suspended from school.

The magnitudes of these effects on test scores are substantively important, especially given that more than one-fifth (21.8 percent) of U.S. schools are within one mile of a TRI site. For example, Chetty, Friedman, and Rockoff (2014) find that a one standard deviation improvement in teacher quality increased test scores by 0.1 standard

35. 9.7 percent of Florida students are absent 21 days or more, so this is a 16 percent increase in the percent of students who are absent more than 21 days.

36. This includes data from people of all ages within a zip code.

deviations. This suggests that removing exposure to pollution would increase test scores as much as increasing teacher quality by 0.24 standard deviations. In addition, after a TRI site opens, PM2.5 in the surrounding neighborhood increases by about 0.1 standard deviations. This implies that a one standard deviation increase in pollution would decrease test scores by 0.24 of a standard deviation. This is a large effect size compared with other school-based interventions. For example, this is comparable in magnitude to the Tennessee STAR experiment (Krueger 1999), which found that reducing class sizes from 22 to 15 students increased test scores by about 0.2 of a standard deviation.

It is difficult to estimate how pollution might affect economic outcomes based on how it affects test scores since there are potential issues with external validity and differences across samples. Nevertheless, we also attempt a rough back-of-the-envelope calculation to estimate the effect of TRI pollution on wages given the effects on test scores.[37] We find that being exposed to TRI pollution in school leads to a US$4,361 decrease in lifetime income per person (in present value terms). Similarly, Isen, Rossin-Slater, and Walker (2017) find that a 10 percent reduction in ambient TSP levels from the Clean Air Act led to a 1 percent increase in mean annual earnings, which suggests that the cumulative lifetime income gain is approximately US$4,300 in present value terms.

Given that our estimate is so similar to that in Isen, Rossin-Slater, and Walker (2017), this suggests that the main mechanism through which air pollution affects earnings is education. Furthermore, this suggests that postnatal exposure might be just as damaging to children's future economic prospects as prenatal exposure. With 436,088 children in Florida ever attending school within one mile of an operating TRI site during this sample period, this result implies US$1,875,178,400 in lost lifetime earnings (if we assume that an increase in pollution leads to a similar lifetime reduction of US$4,300). This figure represents about 26.6 percent of Florida children observed during this time period (1999–2012), and 30 percent of Florida schools had a TRI site operating within one mile of the school. If we divide this figure by the number of TRI sites operating during this time period (881), this implies a cost of US$2,128,466 per TRI site.

Furthermore, this study shows that school locations themselves, even within a zip code, are important determinants of children's and schools' success. Given that geography is an important determinant of human capital formation (Chetty et al. 2014), it is important to understand the mechanisms behind the disparities in educational outcomes that could stem from location itself. Our study suggests that pollution is one such mechanism.

We find strong evidence of lower test scores even though the comparison group is likely exposed to some pollution and parents and teachers might practice avoidance

37. We take the estimate from Chetty, Friedman, and Rockoff (2014) that a one standard deviation increase in test scores is associated with a 0.12 increase in wages at age 28, conditional on ethnicity, gender, age, lagged suspensions and absences, and indicators for grade repetition, free or reduced-price lunch, special education, and limited English, cubic polynomials in prior-year math and English scores, interacted with the student's grade level, and classroom-level controls, grade and year. If we have a −0.024 standard deviation decrease in test scores, a TRI site would decrease annual earnings at 28 by $-0.024 \times 0.12 = 0.00288$, or 0.288 percent. We then calculate expected earnings at 28 by using the March Current Population Survey data to estimate an age–earnings profile using a nonlinear function of age to predict earnings at each age between 18 and 65, assuming a growth rate of real labor productivity growth of 1.9 percent and a discount rate of 3.38 (that is, the 30-year Treasury bond rate) Using these figures, we get a cost estimate very close to the Isen et al. (2017) estimate—we find a US$4,361 decrease in lifetime income per person.

behaviors to reduce children's exposure to pollution. For example, if children who are attending school outside of the one-mile radius around a TRI site are more likely to live within one mile of a TRI site, our results would be biased towards zero. Children also take tests and learn indoors for most of the day in air-conditioned classrooms equipped with air filtration systems, which are shown to improve air quality. Taken together, this suggests that these estimates are lower bounds on the true effect of pollution on children's health and cognitive development. More research should be done on how schools can avoid air pollution through air filtration systems or other mechanisms.

Given that 16 percent of schools in our sample experience a school grade decline per year, this suggests that TRI pollution could account for 18.1 percent of all school grade drops per year (0.029/0.16) over this time period when TRI sites opened. This is a relatively large fraction of school grade drops, with large potential consequences for teachers and students.

Taken together, these findings reveal that school locations on their own contribute to children's cognitive development and schools' success, as well as how exposure to pollutants in schools may result in community-wide impacts on educational policy. This is the first study to investigate the impacts of pollution on a school's overall performance on high-stakes accountability measures, and thus to examine the ways local environmental policy affects education policy. If schools are not fully in control of students' test scores but still face rewards and sanctions for these scores, this raises important questions of fairness, particularly if the schools serving the highest fractions of Black or low-income children are the most affected by local pollution.

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