Published in final edited form as:

Environ Res. 2016 May ; 147: 164–171. doi:10.1016/j.envres.2016.02.004.

School-based Exposure to Hazardous Air Pollutants and Grade Point Average: A multi-level study

Sara E. Grineski[a], **Stephanie E. Clark-Reyna**[b], and **Timothy W. Collins**[c]

Stephanie E. Clark-Reyna: clark.stepha@husky.neu.edu; Timothy W. Collins: twcollins@utep.edu

[a]Department of Sociology and Anthropology. 500 West University Avenue, University of Texas at El Paso, El Paso, TX, USA, 79902. Telephone: 915-747-8471; Fax: 915-747-5505

[b]Department of Sociology and Anthropology. 500 West University Avenue, University of Texas at El Paso, El Paso, TX, USA, 79902

[c]Department of Sociology and Anthropology. 500 West University Avenue, University of Texas at El Paso, El Paso, TX, USA, 79902

Abstract

The problem of environmental health hazards around schools is serious but it has been neglected by researchers and analysts. This is concerning because children are highly susceptible to the effects of chemical hazards. Some ecological studies have demonstrated that higher school-level pollution is associated with lower aggregate school-level standardized test scores at school, likely related to increased respiratory illnesses and/or impaired cognitive development. However, an important question remains unexamined: How do school-level exposures impact individual children's academic performance? To address this, we obtained socio-demographic and grades data from the parents of 1,888 fourth and fifth grade children in the El Paso (Texas, USA) Independent School District in 2012. El Paso is located on the US-side of the Mexican border and has a majority Mexican-origin population. School-based hazardous air pollution (HAP) exposure was calculated using census block-level US Environmental Protection Agency National Air Toxics Assessment risk estimates for respiratory and diesel particulate matter (PM). School-level demographics were obtained from the school district. Multi-level models adjusting for individual-level covariates (e.g., age, sex, race/ethnicity, English proficiency, and economic deprivation) and school-level covariates (e.g., percent of students economically disadvantaged and student-teacher ratio) showed that higher school-level HAPs were associated with lower individual-level grade point averages. An interquartile range increase in school-level HAP exposure was associated with an adjusted 0.11 to 0.40 point decrease in individual students' grade point averages (GPAs), depending on HAP type and emission source. Respiratory risk from HAPs had a larger effect on GPA than did diesel PM risk. Non-road mobile and total respiratory risk had the largest effects on

Corresponding Author: segrineski@utep.edu.

Statement of Approval

The work reported in this manuscript was approved by the University of Texas at El Paso's Institutional Review Board, # 292030-5.

children's GPA of all HAP variables studied and only mother's level of education had a larger effect than those two variables on children's GPA. The five school-level demographic indicators were only weakly associated with GPA. The study findings indicate the need for regulations on school siting and adjacent land uses to protect children's environmental health.

Keywords

Environmental justice; academic performance; hazardous air pollutants; children; schools

1. Introduction

Nearly 600 million children attend primary school worldwide, yet little attention is paid to school-based environmental health hazards confronting them (Legot et al. 2010; Pastor et al. 2002; Sampson 2012). The problem of environmental hazards in and around schools is serious (Rudnai et al., 2012; Wargo 2004). For example, in the US, a significant portion of the top 100 polluting facilities for developmental toxics are located in close proximity to multiple schools (Legot et al. 2010). Children are highly susceptible to the effects of chemical hazards because of heavy exposures (i.e., they consume more air and food per unit of body weight than do adults), biologic sensitivity associated with early growth and development, and their long future lifetimes as early insults can manifest in adult diseases (Perera 2008). The World Health Organization has published guidelines for integrating environmental considerations into school siting policies (Wargo 2004), as has the United States Environmental Protection Agency (USEPA) (Environmental Protection Agency 2014). Because these guidelines are designed to inform voluntary decision-making only, there is no enforcement component. The lack of enforcement is reflected in the fact that only 10 US states actually prohibit school siting near environmental health hazards (Gaffron and Niemeier 2015).

One documented consequence of school-based exposure to environmental health hazards is a reduction in children's aggregate standardized test scores. Subpar academic performance at a young age can have lifelong impacts on a child's developmental trajectory and life chances, including lower economic and educational attainment in adulthood. Statewide in California (USA), hazardous air pollutant (HAP) risks were negative and statistically significant predictors of lower standardized test scores adjusting for school demographics in OLS regression models (Pastor et al. 2006). A more recent study in Sacramento, California found a similar association between school-level PM2.5 and aggregate academic performance (Gaffron and Niemeier 2015). Outside of California (Pastor et al. 2004; Pastor et al. 2006), researchers have examined similar questions in Baton Rouge, Louisiana (USA) based on school proximity measures to Toxic Release Inventory (TRI) facilities. They found that a school's proximity to these industrial facilities was significantly and negatively associated with lower aggregate standardized test scores, controlling for a host of relevant school-level covariates (Legot et al. 2011; Lucier et al. 2011; Scharber et al. 2013). Another study found a similar pattern in Michigan (Mohai et al. 2011).

While documenting a disturbing pattern, this extant literature is limited by ecological study designs. Results obtained solely from aggregate (or ecological) data should not be used for making assumptions about associations at the individual level; doing so commits the ecologic fallacy (Beale et al. 2008). By design, these ecological studies have also neglected factors known to influence children's academic achievement at an individual-level, like mothers' education and family economic status, which confounds reported findings. While ecologic study designs are appropriate when little is known about the association under study, they are less appropriate for examining school-level pollution and academic performance, given the ecologic evidence now available (Currie 2009; Gaffron and Niemeier 2015; Legot et al. 2010; Lucier et al. 2011; Mohai et al. 2011; Pastor et al. 2002; Pastor et al. 2004; Pastor et al. 2006; Scharber et al. 2013).

The important question as to how school-level exposures impact individual children remains unexamined. Individual children have not been studied in the literature likely because of data limitations. Standardized test scores aggregated at the school level are relatively easy to acquire from public sources, whereas academic performance measures and personal characteristics for individual children are more difficult to obtain. The use of individual-level data in a study examining school-level pollution also necessitates a more complex statistical approach, e.g., multi-level modelling (Raudenbush and Bryk 2002), than the OLS regression models used in previous studies examining school-level pollution.

Improving on prior school-level studies, we employ a multi-level modelling approach which allows us to examine the effects of school-level covariates (e.g., level of air pollution at the school, percent of children qualifying for free/reduced price meals) and individual-level control variables (e.g., mother's education) on an individual-level outcome (i.e., child's grade point average [GPA]) for the first time. We do so by integrating primary survey data on El Paso, Texas (USA) school children, school data from the El Paso Independent School District (EPISD), and geographically fine-scale hazardous air pollutant (HAP) data from the USEPA. We answer the following research question: What is the effect of outdoor HAPs surrounding school sites on attending students' GPAs accounting for individual-level covariates and school-level demographics?

2. Materials and Methods

2.1 Study Context

The study was conducted in the El Paso Independent School District, Texas, USA (see Figure 1). El Paso is located on the US-Mexican border and has an estimated population of 640,066 (as of the 2011 American Community Survey). Texas is one of the US states with no policy on school siting, even though the Texas Parent Teacher Association passed a resolution demanding safe school siting throughout the state (Blanchard 2010). El Paso's population is 81% Hispanic; by comparison, 17% of US population and 38% of the Texas population are Hispanic. About 14% of El Paso residents are non-Hispanic white, while 4% are non-Hispanic black. El Paso has a rate of poverty (24% in 2011) that is substantially greater than the national rate (16%).

The EPISD is the 10th largest district in Texas and the 61st largest district in the US, with more than 64,000 students across 94 campuses. Nearly 40% of EPISD students are enrolled in 58 elementary schools, all of which are represented in this study. In terms of the levels of air pollution surrounding the elementary schools, some schools face alarmingly high levels of exposure to HAPs known to be associated with respiratory illness ("respiratory risk") and HAPs found in diesel particulate matter ("diesel PM risk") that are known to cause non-cancerous health effects. All 58 schools have respiratory risk estimates above 1.0 and 27 schools have diesel PM risk values above 1.0; the USEPA indicates that scores above 1.0 demonstrate the potential for adverse health effects (Environmental Protection Agency 2011a).

Demonstrating a pattern of environmental injustice, we observed that school sites with greater exposure to HAP risk were more likely to be poor and minority. Schools with respiratory risk values at or above the mean of 2.0 (n=23) have higher percentages of Hispanic students (95% vs. 75%, p<0.05) and students qualifying for free and reduced price meals (88% vs. 65%, p<0.05) than do the schools with respiratory risk values below the mean (n=35). The schools with diesel PM values at or above 1.0 (n=27) have greater percentages of Hispanic students (90% vs. 77%, p<0.05) and students qualifying for free and reduced price meals (87% vs. 63%, p<0.05) than do the schools with diesel PM values below 1.0 (n=31).

2.2 Data Collection

We used a cross-sectional mail survey to collect individual-level socio-demographic and academic performance measures (Grineski et al. 2014). The survey was sent to all caretakers of fourth and fifth grade student enrollees in the EPISD in 2012. To obtain the highest response rate possible, we employed Dillman et al.'s (2009) Tailored Design Method. We initially mailed out a bilingual (English/Spanish) packet containing a consent form, the questionnaire, a return envelope and a two-dollar incentive. The following week we sent out a bilingual reminder postcard to non-respondents, and the third week, we resent the full packet to all non-respondents. A total of 6,295 surveys were delivered to the children's home address and we received a total of 1,904 responses, which gave us a response rate of 30 percent. Research has shown that similar response rates can yield representative samples (e.g., Keeter et al. 2006) and response rates poorly predict nonresponse bias (Groves and Peytcheva 2008). The sample was generally representative of EPISD fourth and fifth graders in terms of Hispanic ethnicity (82.2% versus 82.6%). The sample was slightly less poor as the percent of students qualifying for free or reduced price meals was 60.0% vs. 71.3% among all EPISD fourth and fifth graders.

The sample was diverse in terms of social class and ethnic status. Overall, 22% of the children's households made less than $10,000 per year while 11% made over $100,000 per year; 21% of households had received public assistance and 16% of children were not covered by health insurance continuously over the past 12 months. Approximately one-quarter of primary caretakers had not graduated from high school (i.e., had completed 11 years of schooling or less). In terms of housing, 49% of children lived in rented homes and the majority (i.e., 62%) of households had lived in El Paso County since their fourth or fifth grade child was born. In terms of factors more closely related to ethnic status, 79% of primary caretakers and 82% of children were Hispanic, with 72% and 71%, respectively, identifying as Mexican-origin Hispanics. In terms of nativity, 50% of primary caretakers and

10% of children were foreign-born, while 30% and 5%, respectively, were not US citizens. Approximately two-thirds of the primary caretakers' parents were foreign-born. Among foreign-born primary caretakers, the median length of residence in the US was 16 years.

School-level demographic data were obtained from the EPISD through an open records request. We received 2012 school-level demographic information for all fourth and fifth grade classes to coincide with the timing of the survey.

School-level pollution values were created from the USEPA's 2005 National Air Toxics Assessment (NATA) census block-level database. We received the census-block level estimates directly from the USEPA and they are at a finer spatial resolution than the publically available census tract estimates used to assign risk values to specific locations in other studies (e.g., Roberts et al. 2013). The NATA includes all HAPs regulated by the US Clean Air Act (except criteria pollutants) that are known or suspected to cause cancer or neurological, respiratory and immunological diseases as well as reproductive ailments (Environmental Protection Agency 2011b). NATA is currently the best available secondary data source for spatially explicit characterization of HAP exposure risk in US metropolitan areas. The USEPA works with states and industries to gather data about HAP emissions and then compiles them in the NATA. The methodology used models the risks of different pollutants additively and sums them to estimate an aggregate risk score for each geographic unit. Information about the modelling is explained elsewhere (Environmental Protection Agency 2011c).

2.3 Level 1 Variables

2.3.1 Dependent Variable—Children's Academic Performance Grade point average (GPA) was used to measure children's academic performance. GPA was calculated based on a survey question derived from an EPISD report card: "what grades has your child received in the following subject areas: reading, language arts, math, social studies, and science? For each subject area, the response options were: A=90–100; B=80–89; C=75–79; D=70–74; or F=0–69. We then recoded each subject area so that F=0; D=1; C=2; B=3; and A=4. The subject area scores were summed and divided by five to create the continuous GPA variable (Clark-Reyna et al. 2015). Children performed well in school as the mean GPA was 3.3 out of 4.0. While likely demonstrating grade inflation, this grade distribution mirrors the national grading pattern for elementary schools. According to the US Department of Education (2009), 82% of students received either mostly A's or mostly B's nationwide in 2009 and 78% of children in our sample had GPAs above 3.0.

2.3.2 Independent Variables—We adjust for eight individual-level control variables based on a review of the academic performance literature. See Table 1 for information about the variables and Table 2 for descriptive statistics. We drew on data from the primary caretaker and the secondary caretaker to create variables for the child's mother, since the mother was typically listed as the primary caretaker or the secondary caretaker, depending on the family surveyed. To summarize the descriptive statistics, 60% of children qualified for free/reduced priced meals at school. The average age of the children was 10 with a range of 8 to 13. Half of the students were male. While only 2% of mothers were non-Hispanic black, four-fifths were Hispanic. On average, mothers completed one year of education beyond high school and scored "well" in terms of English speaking proficiency. Nearly one-tenth of mothers was teenage when giving birth to the child.

2.4 Level 2 Variables

2.4.1 HAP Variables—We used the respiratory and diesel particulate matter HAP risk estimates from the NATA, which are disaggregated by emission source (see Table 2). We use (1) total respiratory risk, which is the summation of estimated respiratory risks from all HAP emission sources (mapped in Figure 1); (2) on-road mobile respiratory risk, which includes only risks due to emissions from vehicles found on roads such as cars, trucks, and buses; and (3) non-road mobile respiratory risk, which includes only risks attributable to emissions from mobile sources not found on roadways, e.g., airplanes, trains, and construction vehicles (Environmental Protection Agency 2011a). Additionally, we include the diesel risk variables of (4) total diesel particulate matter (PM), (5) on-road diesel PM and (6) non-road diesel PM, which include only non-carcinogenic health effects. To account for the level of HAP exposures at each school, we used a point-in-polygon approach to assign values to each elementary school based on the NATA risk estimates for the census block in which each school was located.

The units for the respiratory and diesel PM risk variables are based on what the USEPA terms a "hazard index" (HI). The units for the HI are different than the units for the cancer risk estimates in the NATA, which are measured using an "N" in a million (Environmental Protection Agency 2011a). The HI is calculated using the inhalation reference concentration (RfC) for each pollutant. The RfC is the amount of toxicity below which long-term exposure to the general population is not expected to result in adverse effects (Pastor et al. 2006). The EPA uses the RfC as part of a calculation called the hazard quotient, which is the ratio between the concentration to which a person is exposed and the RfC. The combined risk associated with inhalation exposure in each geographic unit is measured with the HI, defined as the sum of hazard quotients for individual HAPs that affect the same target organ (e.g., lung). The HI is only an approximation of the aggregate effect on the target organ, because some pollutants may operate synergistically. Although the HI cannot be translated to a probability of an adverse effect, a HI greater than 1.0 indicates the potential for harm, and a higher HI indicates greater potential for adverse effects (Environmental Protection Agency 2011a). In the statistical analysis, the natural log of each HI is used due to skewness and kurtosis.

2.4.2 School Demographics—Apart from school-level HAPs, we analyze five additional school-level variables (see Table 2) selected based on prior studies. First, we consider the total enrollment at each school (Scharber et al. 2013). Second, we use the percentage of students qualifying for free and reduced price meals as the measure of economic deprivation (Pastor et al. 2006; Scharber et al. 2013). To operationalize teacher quality (Pastor et al. 2006), we use the percentage of teachers with a Master's degree. Fourth, we include the student-teacher ratio, which is reflective of school resources (Lucier et al. 2011). Fifth, we consider percentage of students in special education to represent the prevalence of students with disabilities (Legot et al. 2011; Lucier et al. 2011; Scharber et al.

2013). A race/ethnicity variable [e.g., percentage nonwhite students (Lucier et al. 2011; Scharber et al. 2013)] was excluded from the statistical analysis due to collinearity with free/reduced price meals, e.g., the two variables were correlated at 0.757 ($p<0.001$). We selected economic deprivation over the race/ethnicity variable, since it has been argued that economic status is the most important control variable in these studies (Pastor et al. 2006; Scharber et al. 2013).

2.5 Analysis Methods

Our data had a multi-level structure, with 1,888 individuals at level 1 nested within 58 elementary schools at level 2. Before beginning the analysis, 16 children were removed from original individual-level data file (n=1,904): six lived outside of the county limits; two attended an alternative school; one was being home-schooled at the time of the survey; and seven were excluded because they attended a recently closed school, which was missing in the school-level dataset.

Multiple imputation (MI) was applied to the individual-level dataset to address missing values and non-response bias. Statistics for percent missing of each variable are included in Table 2. The multiply imputed data were analyzed using HLM7 software. MI uses a regression-based approach to create multiple sets of values for missing observations. It avoids the bias that can occur when missing values are not missing completely at random and is appropriate for self-reported survey data (Enders 2010). In IBM SPSS Statistics 21, ten imputed datasets were specified to increase power and 200 between-imputation iterations were used to ensure that the resulting imputations were independent of each other. HLM7 analyzed each of the ten individual-level datasets separately, and then calculated pooled results.

To account for potential school variation in GPA, we adopted a multi-level regression modeling approach. The principles and relevance of multi-level modeling for analyzing clustered data have been thoroughly described elsewhere (Raudenbush and Bryk 2002). The generic model was specified as a continuous response (i.e., GPA), for individuals attending a school, our cluster definition. The equation consisted of fixed effects and random effects attributable to school clusters. All models rely on robust standard error estimates, which are relatively insensitive to the misspecification of variance and covariance at both the individual and school levels and their respective distribution assumptions (Raudenbush and Bryk 2002). School-level variables use a standardized metric (mean=0, SD=1), specifically grand mean centering, while individual-level variables do not.

In total, we estimated six models. The dependent variable in each is GPA but we rotated one of the six HAP variables, and included each alongside the eight individual-level controls and five school-level demographic variables. We did not include the HAP variables together in the same model due to their potential collinearity.

3. Results

Table 3 presents results for the six models. All six HAP variables were positively related to GPA. The magnitude of some HAP coefficients is notable. A one standard deviation increase in the natural log of total respiratory risk was associated with a 0.26 (95% CI: −0.40, −0.11) point drop in GPA. A one standard deviation increase in the natural log of non-road mobile respiratory risk was associated with a 0.18 (−0.29, −0.08) point drop in GPA. Non-road diesel had the weakest association with GPA of the six variables examined.

While Table 3 reports effects on GPA in terms of standard deviation increases in HAPs, an interquartile range (IQR) increase is also illustrative. In terms of decreases in GPA per IQR increase in each HAP variable (not shown in tables), the decreases are −0.403 (95% CI: −0.635, −0.173) points for a IQR increase in total respiratory risk, −0.169 (−0.295, −0.044) for on-road respiratory risk; −0.203 (−0.315, −0.091) for non-road respiratory risk; −0.222 (−0.371, −0.072) for total diesel PM risk; −0.164 (−0.289, −0.040) for on-road diesel PM risk; and −0.105 (−0.257, −0.047) for non-road diesel PM risk. In terms of other school-level effects, the five demographic variables were only weakly related to GPA.

At the individual-level and across the six models, qualifying for free/reduced price meals and being a boy were associated with significantly lower GPAs. Having a mother with higher levels of education and with greater English proficiency were positive and significant influences on GPA. Based on t-ratio values, the mother's level of education was the most important predictor of GPA, followed by two school-level pollution variables (non-road respiratory risk and total respiratory risk).

The intercept variable component in all six models (not shown in Table 3) demonstrated that there were significant school effects on GPA and that multi-level models are appropriate for these data. For the respiratory risk models, the chi-square values for the intercept variable component were 82.163 (p=0.004); 88.685 (p=0.001); and 81.488 (p=0.004) respectively. For the intercept variable component in the diesel PM models, the chi-square values were 86.127 (p=0.002), 88.916 (p=0.001) and 90.061 (p=0.001).

As a sensitivity analysis, we ran the same set of models using "percent nonwhite" in place of "percent free/reduced price meals". The results were nearly identical in terms of the effect of school HAPs on GPA and "percent nonwhite" being a positive but unimportant predictor of individual GPA.

4. Discussion

Our multi-level modeling results align with the association between school-level pollutant exposure and aggregated school performance measures found in studies using ecological designs. In the multi-level models employed here, the HAP variables measured at the level of the school were associated with lower GPAs among children at the individual level. In comparing the findings for respiratory risk to diesel PM, respiratory risk from HAPs had a larger effect on GPA than did diesel PM risk. Non-road mobile and total respiratory risk had the largest effects on children's GPA of all HAP variables studied and only mother's level of education had a larger effect than those two variables on children's GPA. The five school-level demographic indicators were only weakly associated with GPA, suggesting that individual-level demographic characteristics have more powerful effects on children's GPAs than do school-level demographics.

The association between greater HAP exposure at school and a reduction in GPA among school children may be shaped by two potential mechanisms, which should be explored in future studies. First, a hypothesis forwarded in the environmental justice literature is that poorer air quality is linked to increases in respiratory illnesses, which results in school absenteeism, and diminished academic performance (Pastor et al. 2002, 2004, 2006; Lucier et al., 2011). In support of this hypothesis are those studies linking exposure to air pollution to increases in respiratory infections and asthma (Belleudi et al. 2010; Grineski et al. 2010; Peden 2015; Ghosh et al., 2016) and those associating exposure to air pollution with increased absenteeism (Currie 2009; Gilliland et al. 2001). However, the link between asthma and poorer school performance is tenuous. In a literature review published in 2005, approximately two-thirds of the 36 studies reviewed found no significant associations between asthma and poorer school performance; those studies finding significant associations were examining severe and persistent symptoms (Taras and Potts-Datema 2005). More recently, two longitudinal studies did uncover associations between children's asthma symptoms and lower standardized test scores in the Netherlands (Ruijsbroek et al., 2015) and having asthma as a child and lower long-term educational attainment in the US (Champaloux and Young, 2015).

A second hypothesis is that when children are chronically exposed to HAPs, their cognitive development is delayed or impaired (Calderón-Garcidueñas et al. 2008, 2012; Guxens and Sunyer 2012). Based on autopsies of otherwise clinically healthy Mexico City youth, Calderón-Garciduenas and her colleagues (2008, 2012) demonstrated that exposure to high levels of air pollution produces neuroinflammation and altered innate immune responses in crucial brain areas in children and young adults. Some of the youth exposed to high levels of air pollution had brain structures that were beginning to resemble those with early stage Alzheimer's disease (Calderón-Garcidueñas et al. 2008; 2012).

These two hypothetical mechanisms may not be mutually exclusive. Respiratory and developmental effects of air pollution may operate synergistically to impair children's academic performance. One of the mechanisms linking air pollution to neurodegeneration is through injury to the lung epithelial and endothelial cells, which causes persistent chronic inflammation in the respiratory tract. In addition to causing respiratory symptoms, this is linked to systemic inflammation and chronic oxidative stress, which can cause DNA oxidative damage in critical areas of the developing brain areas as well as outside the central nervous system (Calderón-Garcidueñas et al. 2008).

Given this proposed neurological pathway between HAP-exposure and GPA, the individual-level demographic factors that were significantly associated with GPA in this analysis can be considered hypothetical neuroprotective factors, being that they were significantly related to GPA even after controlling for school-level HAPs. Regardless of the level of HAP at the school, when the child comes from a household that does not qualify for free/reduced price meals, is a girl, and has a mother with higher educational attainment and greater English proficiency, he/she tends to do better in school. This suggests that these attributes may buffer the child against some of the negative consequences of attending a school with high levels of ambient HAP exposure. Practically, however, it is more likely that low socioeconomic status and racial/ethnic minority students will be attending schools with higher levels of HAPs; this is the case in El Paso (as reported earlier in this paper) and elsewhere (Chakraborty and Zandbergen 2007).

Conversely, it seems as if exposure to air toxics likely compounds the learning challenges faced by the average EPISD student, who comes from a low-income, limited English background and may already be struggling in school. He/she may also lack access to regular healthcare. Children in this sample did report greater cost-related barriers to accessing health care than did US Hispanic children more generally (Balcazar et al. 2015). The confluence of social and environmental risk factors creates a situation of 'multiple jeopardy' for many El Paso school children (Clark-Reyna et al. 2015). The reduced GPA among children exposed to HAPs at school is a disadvantage that contributes to an uneven playing field, which further decreases these children's life chances, compared to their more advantaged counterparts.

In terms of study limitations, a longitudinal approach would have allowed for stronger inferences regarding causal pathways, but we were limited by the cross-sectional nature of our data. A multimodal data collection strategy would likely have improved the response rate, which was 30%. While children were generally representative of EPISD fourth and fifth graders in terms of ethnicity, they experienced lower levels of economic deprivation than their EPISD counterparts (i.e., 60% qualifying for free/reduced price meals vs. 71%). Given that we are underestimating the level of poverty in the district, we may be underestimating relationships between HAP exposure and academic achievement. It may also be the case that we are not capturing unauthorized immigrant children and citizen children from unauthorized families in our sample, since their parents would be less likely to complete a survey. While no estimates are available from EPISD, according to the Center for Migrant Studies (2015), 68,699 residents of El Paso County were unauthorized migrants in 2013. Pairing this with population statistics for the county, we can determine that approximately 8% of county residents are unauthorized and that a third of all foreign-born residents are unauthorized. However, only 12% of unauthorized residents in the county are children (ages 5–17) (Center for Migrant Studies, 2015), and so we can estimate based on population data that 5% of all children in the county are unauthorized. While their experiences are important to capture, these unauthorized children do not represent a significant proportion of our sampling frame. Relatedly, we did not ask about undocumented status on our survey due to the preferences of the EPISD.

While a multi-level model permits the inclusion of home and school HAP exposure in the same model, we were unable to consider both due to collinearity, even though home site HAP exposure significantly influences children's GPA (Clark-Reyna et al. 2015). This study focused on a single setting and findings may not be generalizable to other settings. Like other pollution/academic performance studies, this one was conducted in the US; future research should be done in other countries to examine similarities and differences across varying educational system and environmental policy contexts.

There are also limitations associated with using USEPA NATA data. We paired the 2005 estimates, which were the most recent available at the time of the study, with survey data from 2012, although we do believe that the distribution of NATA values is relatively constant between 2005 and 2012. This is because all major freeways, roads, factories, refineries, airports, train stations, and ports of entry within the EPISD have remained in the same location since before 2005. Additionally, the NATA focused on inhalation exposure, which neglects exposure through skin contact or ingestion. It does not include criteria pollutants, which are an important source of risk, nor does it consider possible synergistic effects.

5. Conclusion

This study methodologically improves upon prior studies and contributes to the mounting evidence suggesting that school siting and land use regulations are needed to better protect children from the effects of air pollution on their health, development, and (future) well-being (Clark-Reyna et al. 2015; Currie 2009; Gaffron and Niemeier 2015; Legot et al. 2010; Lucier et al. 2011; Mohai et al. 2011; Pastor et al. 2002; Pastor et al. 2004; Pastor et al. 2006; Scharber et al. 2013). While the WHO (Wargo 2004) and US EPA (Environmental Protection Agency 2014) recommendations for school siting are well-founded, voluntary guidelines are not proving to be enough to influence the locational decision-making process in a manner that promotes environmental health and justice for children.

Acknowledgments

Statement of Funding

This work was jointly supported by the National Institute of Minority Health and Health Disparities (NIMHD) and the United States Environmental Protection Agency [Award Number P20 MD002287-05S1]. The content is solely the responsibility of the authors and does not necessarily represent the official views of the NIMHD or the EPA.

We recognize assistance from Marilyn Montgomery, who prepared the block level NATA data for us. We thank Bibi Mancera and Zuleika Ramirez at the Hispanic Health Disparities Center and the staff at the UTEP Campus Post Office for their assistance in carrying out the survey. The research participants are also gratefully recognized for taking the time to complete the survey. The work of student research assistants Anthony Jimenez, Marie Gaines, Paola Chavez-Payan, Alexander Balcazar, and Young-an Kim is gratefully recognized.

References

Balcazar A, Grineski SE, Collins T. The durability of immigration related barriers to healthcare access for Hispanics across generations. Hispanic Journal of Behavioral Science. 2015; 37:118–135.

Beale L, Abellan JJ, Hodgson S, Jarup L. Methodologic issues and approaches to spatial epidemiology. Environmental Health Perspectives. 2008; 116:1105–1110. [PubMed: 18709139]

Belleudi V, Faustini A, Stafoggia M, Cattani G, Marconi A, Perucci CA, et al. Impact of fine and ultrafine particles on emergency hospital admissions for cardiac and respiratory diseases. Epidemiology. 2010; 21:414–423. [PubMed: 20386174]

Blanchard, R. [accessed 25 August 2015] Texas PTA champions safe school siting. 2010. Available: https://www.momsrising.org/blog/texas-pta-champions-safe-school-siting

Calderón-Garcidueñas L, Solt AC, Henriquez-Roldan C, Torres-Jardon R, Nuse B, Herritt L, et al. Long-term air pollution exposure is associated with neuroinflammation, an altered innate immune response, disruption of the blood-brain barrier, ultrafine particulate deposition, and accumulation of amyloid beta-42 and alpha-synuclein in children and young adults. Toxicologic Pathology. 2008; 36:289–310. [PubMed: 18349428]

Calderón-Garcidueñas L, Kavanaugh M, Block M, D'Angiulli A, Delgado-Chávez R, Torres-Jardón R, González-Maciel A, Reynoso-Robles R, Osnaya N, Villarreal-Calderon R, Guo R. Neuroinflammation, hyperphosphorylated tau, diffuse amyloid plaques, and down-regulation of the cellular prion protein in air pollution exposed children and young adults. Journal of Alzheimer's Disease. 2012; 28(1):93–107.

Center for Migrant Studies. Estimates of the unathorized popualtion by PUMAS, 2010 to 2013. 2015. Available: http://data.cmsny.org/puma.html

Champaloux SW, Young DR. Childhood chronic health conditions and educational attainment: a social ecological approach. Journal of Adolescent Health. 2015; 56(1):98–105. [PubMed: 25305800]

Chakraborty J, Zandbergen PA. Children at risk: measuring racial/ethnic disparities in potential exposure to air pollution at school and home. Journal of Epidemiology and Community Health. 2007; 61(12):1074–1079. [PubMed: 18000130]

Clark-Reyna SE, Grineski SE, Collins TW. Residential exposure to air toxics is linked to lower grade point averages among school children in El Paso, Texas, USA. Population and Environment. 201510.1007/s11111-015-0241-8

Crosser SL. Summer birth date children: Kindergarten entrance age, and academic achievement. The Journal of Educational Research. 1991; 84:140–146.

Currie J, Hanushek E, Kahn M, Neidell M, Rivkin S. Does pollution increase school absences? The Review of Economics and Statistics. 2009; 91:682–694.

Dillman, DA.; Smyth, JD.; Christian, LM. Internet, mail, and mixed-mode surveys: The tailored design method. 3. Hoboken, New Jersey: John Wiley & Sons; 2009.

Enders, CK. Applied missing data analysis. New York: Guilford Press; 2010.

Environmental Protection Agency. [accessed 25 January 2016] Glossary of key terms. 2011a. Available: http://www.epa.gov/national-air-toxics-assessment/nata-glossary-terms

Environmental Protection Agency. [accessed 25 January 2016] 2005 National-scale Air Toxics Assessment. 2011b. Available: http://www.epa.gov/national-air-toxics-assessment/2005-national-air-toxics-assessment

Environmental Protection Agency. [accessed 25 January 2016] An overview of methods for EPA's National-scale Air Toxics Assessment. 2011c. Available: http://www3.epa.gov/ttn/atw/nata2005/05pdf/nata_tmd.pdf

Environmental Protection Agency. [accessed 20 July 2015] School siting guidelines. 2014. Available: http://www.epa.gov/schools/guidelinestools/siting/index.html

Fortin NM, Oreopoulos P, Phipps S. Leaving boys behind: Gender disparities in high academic achievement. Journal of Human Resources. 2015; 50:549–579.

Gaffron P, Niemeier D. School locations and traffic emissions - environmental (in)justice findings using a new screening method. International Journal of Environmental Research and Public Health. 2015; 12:2009–2025. [PubMed: 25679341]

Ghosh R, Rossner P, Honkova K, Dostal M, Sram RJ, Hertz-Picciotto I. Air pollution and childhood bronchitis: Interaction with xenobiotic, immune regulatory and DNA repair genes. Environment International. 2016; 87:94–100. [PubMed: 26655675]

Gilliland FD, Berhane K, Rappaport EB, Thomas DC, Avol E, Gauderman WJ, et al. Effects of ambient air pollution in school absenteeism due to respiratory illness. Epidemiology. 2001; 12:43–54. [PubMed: 11138819]

Grineski SE, Staniswalis JG, Peng Y, Atkinson-Palombo C. Children's asthma hospitalizations and relative risk due to nitrogen dioxide (NO_2): Effect modification by race, ethnicity and insurance status. Environmental Research. 2010; 110:178–188. [PubMed: 19944410]

Grineski SE, Collins TW, Chavez-Payan P, Jimenez AJ, Clark-Reyna SE, Gaines MI, et al. Social disparities in children's respiratory health in El Paso, Texas. International Journal of Environmental Research and Public Health. 2014; 11:2941–2957. [PubMed: 24619157]

Groves R, Peytcheva E. The impact of nonresponse rates on nonresponse bias: A meta-analysis. Public Opinion Quarterly. 2008; 72:167–189.

Guxens M, Sunyer J. A review of epidemiological studies on neuropsychological effects of air pollution. Swiss Medical Weekly: The European Journal of Medical Sciences. 2012; 141

Kao G, Thompson JS. Racial and ethnic stratification in educational achievement and attainment. Annual Review of Sociology. 2003; 29:417–442.

Keeter S, Kennedy C, Dimock M, Best J, Craighill P. Gauging the impact of growing non response on estimates from a national RDD telephone survey. Public Opinion Quarterly. 2006; 70:759–779.

Legot C, London B, Shandra J. Environmental ascription: High-volume polluters, schools, and human capital. Organization & Environment. 2010; 23:271–290.

Legot C, London B, Shandra J. Proximity to industrial toxins and childhood respiratory, developmental, and neurological diseases: Environmental ascription in East Baton Rouge Parish, Louisiana. Population and Environment. 2011; 33:333–346.

Levine JA, Pollack H, Comfort ME. Academic and behavioral outcomes among the children of young mothers. Journal of Marriage and Family. 2001; 63(2):355–369.

Lucier C, Rosofsky A, London B, Scharber H, Shandra J. Toxic pollution and school performance scores: Environmental ascription in East Baton Rouge Parish, Louisiana. Organization & Environment. 2011; 24:423–443.

Magnuson K. Maternal education and children's academic achievement during middle childhood. Developmental Psychology. 2007; 43:1497–1512. [PubMed: 18020827]

Magzamen S, Amato MS, Imm P, Havlena JA, Coons MJ, Anderson HA, Kanarek MS, Moore CF. Quantile regression in environmental health: Early life lead exposure and end-of-grade exams. Environmental Research. 2015; 137:108–19. [PubMed: 25531815]

Mohai P, Kweon B-S, Lee S, Ard K. Air pollution around schools is linked to poorer student health and academic performance. Health Affairs. 2011; 30:852–862. [PubMed: 21543420]

Pastor M, Sadd JL, Morello-Frosch R. Who's minding the kids? Pollution, public schools, and environmental justice in Los Angeles. Social Science Quarterly. 2002; 83:263–280.

Pastor M, Sadd JL, Morello-Frosch R. Reading, writing, and toxics: Children's health, academic performance, and environmental justice in Los Angeles. Environment and Planning C. 2004; 22:271–290.

Pastor M, Morello-Frosch R, Sadd JL. Breathless: Schools, air toxics, and environmental justice in California. Policy Studies Journal. 2006; 34:337–362.

Peden, DB. In Air Pollution and Health Effects. Springer; London: 2015. Air Pollution and Asthma; p. 93-117.

Perera F. Children are likely to suffer most from our fossil fuel addiction. Environmental Health Perspectives. 2008; 116:987–990. [PubMed: 18709169]

Raudenbush, SW.; Bryk, AS. Hierarchical linear models: Applications and data analysis methods. Thousand Oaks: Sage; 2002.

Reardon SF, Galindo C. The Hispanic-white achievement gap in math and reading in the elementary grades. American Educational Reseach Journal. 2009; 46:853–891.

Roberts AL, Lyall K, Hart JE, Laden F, Just AC, Bobb JF, et al. Perinatal air pollutant exposures and autism spectrum disorder in the children of nurses' health study II participants. Environmental Health Perspectives. 2013; 121:978–984. [PubMed: 23816781]

Rudnai P, Csobod E, Vaskovi E, Neri M, Varro M, Sinisi, Luciana L, Cani E, Dragonic J, Korac Z, Hudek V, Halzlova K. School Environment and Respiratory Health of Children (The SEARCH Study). Epidemiology. 2012; 23(5S):S238.

Ruijsbroek A, Wijga AH, Gehring U, Kerkhof M, Droomers M. School Performance: A Matter of Health or Socio-Economic Background? Findings from the PIAMA Birth Cohort Study. PloS one. 2015; 10(8):e0134780. [PubMed: 26247468]

Sampson N. Environmental justice at school: Understanding research, policy, and practice to improve our children's health. Journal of School Health. 2012; 82:246–252. [PubMed: 22494096]

Scharber H, Lucier C, London B, Rosofsky A, Shandra J. The consequences of exposure to, neurological, and respiratory toxins for school performance: A closer look at environmental ascription in East Baton Rouge, Louisiana. Population and Environment. 2013; 35:205–224.

Taras H, Potts-Datema W. Childhood asthma and student performance at school. Journal of School Health. 2005; 75:296–312. [PubMed: 16179080]

US-Mexico Border Health Commission. Health Disparities and the US-México Border: Challenges and Opportunities. The United States-México Border Health Commission; El Paso, TX, USA: 2010. Available: http://www.borderhealth.org/files/res_1719.pdf

US Department of Education. Digest of education statistics. National Center for Education Statistics; 2009. Table 225.80Available: http://nces.ed.gov/programs/digest/d13/tables/dt13_225.80.asp

Wargo, J. [accessed 6 August 2015 2015] The physical school environment: An essential component of a health-promoting school. 2004. Available: http://www.who.int/school_youth_health/media/en/physical_sch_environment.pdf

Highlights

- School-level hazardous air pollutants (HAPs) impact children's academic performance
- Interquartile range increases in HAPs were linked to .1–.4 point decreases in GPA
- Respiratory risk from HAPs had a larger effect on GPA than did diesel PM risk
- Mother's level of education had the strongest effect on GPA

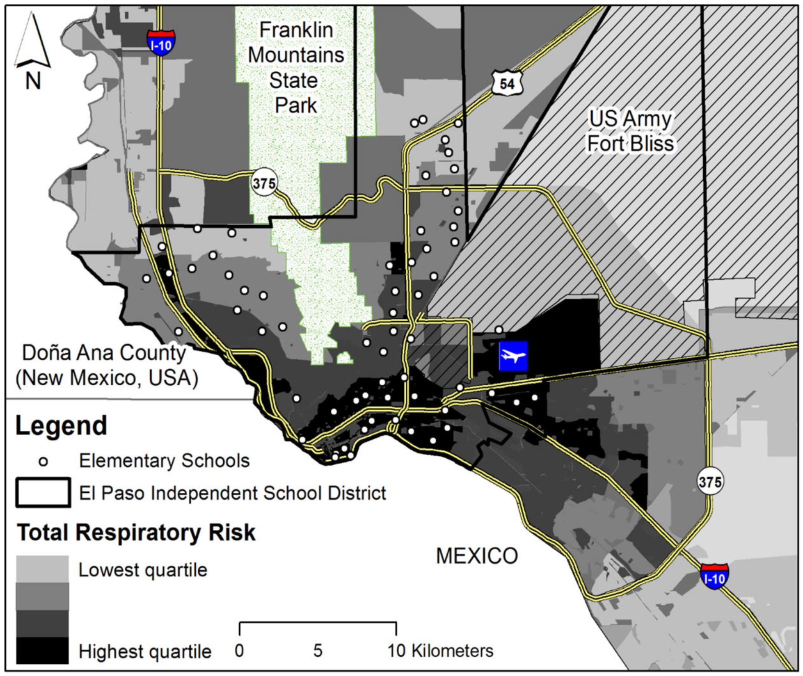

Figure 1.
Study Area and Elementary Schools in El Paso, TX

Author Manuscript

Author Manuscript

Author Manuscript

Table 1

Information about level 1 independent variables

Variable	Survey Question Used	Coding	Justification
Free or Reduced Price Meals (FRPM)	1) How many people are living or staying at this address? 2) What is your yearly total household income for 2011 before taxes (1=Less than $1,999 to 15= $150,000 or more)?" We used US Food and Nutrition Service of US Department of Agriculture guidelines to construct the FRPM variable.	0=not qualifying for free or reduced price meals; 1=qualifying for free or reduced price meals	Economic deprivation has been linked to decreased academic performance (Reardon and Galindo 2009; Magzamen et al., 2015).
Mother's Education	What is the highest level of schooling that you have completed?	1 year to 21 years	Children with well-educated mothers tend to perform better in school than do those with less educated mothers (Ruijsbroek et al., 2015).
Teen Mother	1) What is your age? 2) What is the child's age? Mother's current age was subtracted from child's current age.	1=teenage mother (19 and younger); 0=not a teenage mother (20 years and older).	Children born to teen mothers fare worse in school (Levine, Pollack and Comfort, 2001; Magnuson 2007).
Race/ethnicity: Hispanic or Non-Hispanic Black	1) Are you of Hispanic, Latino, or Spanish origin?" 2) "What is your race?"	1=Hispanic; 0=no 1=non-Hispanic black; 0=no	There is an achievement gap between students of color and white students (Kao and Thompson 2003; Reardon and Galindo 2009).
Mother's English Proficiency	How well do you speak English?	0=not at all; 1=not well; 2=well; and 3=very well.	Mothers who are not proficient in English may be less able to help their children with homework and/or less familiar with the US public school system and its expectations (Reardon and Galindo 2009).
Child's Age	What is the child's age?	8 to 13	Older children do better in school than younger children (Crosser 1991).
Child's Sex	What is the child's sex?	0=female; 1=male	Girls do better in school than boys (Fortin et al. 2015; Magzamen et al., 2015).

Table 2

Descriptive statistics

	Variable	N	Mean		Min.	Max.	IQR[2]	Missing
LEVEL 2	Total RR (ln)	58	0.62	0.39	0.05	1.93	0.61	0
	Total RR[1]	58	2.01	0.96	1.05	6.88	1.16	0
	On Road RR (ln)	58	−0.57	0.76	−1.51	1.68	1.33	0
	On Road RR[1]	58	0.78	0.80	0.22	5.39	0.84	0
	Non Road RR (ln)	58	−1.78	0.52	−3	−0.49	0.57	0
	Non Road RR[1]	58	0.19	0.11	0.05	0.61	0.10	0
	Total Diesel PM (ln)	58	0.08	0.67	−0.8	2.07	1.16	0
	Total Diesel PM[1]	58	1.39	1.21	0.45	7.93	1.39	0
	On Road Diesel PM (ln)	58	−0.27	0.77	−1.24	2.01	1.36	0
	On Road Diesel PM[1]	58	1.07	1.11	0.29	7.49	1.16	0
	Non Road Diesel PM (ln)	58	−1.24	0.58	−2.41	0.85	0.59	0
	Non Road Diesel PM[1]	58	0.35	0.33	0.09	2.34	0.16	0
	Total School Enrollment	58	546	129	273	840	192.25	0
	% Free/Reduced Price Meals	58	74.06	22.77	15.43	99.43	39.65	0
	Student/Teacher Ratio	58	20.21	1.8	15.68	23.73	2.41	0
	% Special Education	58	10.97	4.87	.266	27.02	4.89	0
	% Teachers with MA Degree	58	24.45	17.46	0	66.5	23.96	0
LEVEL 1	Child Sex	1828	0.5	0.5	0	1	n/a	3.2
	Child Age	1856	10.39	0.77	8	13	1	1.7
	Free/Reduced Price Meals	1650	0.60	0.49	0	1	n/a	12.6
	Teen Mother	1625	0.09	0.28	0	1	n/a	13.9
	Mother's Education	1685	13.07	3.88	1	21	4	10.8
	Mother is Hispanic	1666	0.8	0.4	0	1	n/a	11.8
	Mother is Black	1694	0.02	0.15	0	1	n/a	10.3
	Mother's English Proficiency	1649	2.17	1.03	0	3	2	12.7
	Child's GPA	1683	3.32	0.66	0.2	4	1	10.9

[1]This variable was not used in the statistical models, since a natural log transformation was needed to reduce skewness and kurtosis. It is included here since the values are more meaningful when interpreted than the transformed version.

[2]Interquartile range, n/a= not applicable to dichotomous variables

Table 3

Results for individual-level GPA regressed on school-level and individual-level characteristics

	Coefficient (95% Confidence Interval)	Stand. Error	t-ratio	p-value
Intercept	3.214 (2.516, 3.866)	0.333	9.654	<0.001
School Pollution[a]				
Total RR (ln)	−0.256 (−0.403, −0.110)	0.075	−3.427	0.001
On-Road RR (ln)	−0.097 (−0.169, −0.025)	0.037	−2.643	0.011
Non-Road RR (ln)	−0.184 (−0.285, −0.082)	0.052	−3.546	<0.001
Total Diesel PM (ln)	−0.128 (−0.214, −0.042)	0.044	−2.908	0.005
On-Road Diesel PM (ln)	−0.093 (−0.164, −0.023)	0.036	−2.594	0.012
Non-Road Diesel PM (ln)	−0.102 (−0.251, 0.046)	0.076	−1.356	0.181
School Covariates[b]				
Total Enrollment	−0.001 (−0.001, 0.003)	0.001	−0.473	0.638
% Free/Reduced Price Meals	−0.001 (−0.003, 0.002)	0.001	−0.479	0.634
Student/Teacher Ratio	0.000 (−0.028, 0.028)	0.014	0.008	0.994
% Special Education	−0.008 (−0.005, 0.002)	0.006	−1.464	0.149
% Teachers with MA Degree	−0.002 (−0.019, 0.003)	0.002	−0.893	0.376
Individual Covariates[c]				
Child’s Sex (Male)	−0.091 (−0.162, −0.019)	0.036	−2.490	0.013
Child’s Age	−0.047 (−0.103, 0.008)	0.028	−1.668	0.096
Free/Reduced Price Meals	−0.213 (−0.367, −0.059)	0.079	−2.706	0.013
Teen Mother	−0.024 (−0.086, 0.037)	0.031	−0.775	0.446
Mother’s Education	0.047 (0.029, 0.065)	0.009	5.221	<0.001
Mother is Hispanic	−0.176 (−0.378, 0.025)	0.103	−1.716	0.107
Mother is Black	−0.285 (−0.718, 0.149)	0.221	−1.287	0.222
Mother’s English Proficiency	0.054 (0.006, 0.102)	0.024	2.207	0.032

NOTES: Neighborhood-level N=58; Individual-level N=1,888; Models estimated with robust standard errors.

[a]Each pollution variable was included in a separate modelling run. All six models included the school-level demographic and individual-level covariates. All pollution covariates were grand mean centered.

[b]Results reported are for the model including total respiratory risk (“Total RR (ln)”). Results for the school-level covariates are the same in terms of direction and significance across all six models with the exception of “% Special Education” which approaches statistical significance (p<.10) in the models including “Non-Road RR (ln)” and “Non-Road Diesel PM (ln)”. All school-level covariates were grand mean centered.

[c]Results reported are for the model including “Total RR (ln)”. Results for the individual-level covariates are the same in terms of direction and significance across all six models.