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Residential exposure to air toxics is linked to lower grade point averages among school children in El Paso, Texas, USA

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Abstract

Children in low-income neighborhoods tend to be disproportionately exposed to environmental toxicants. This is cause for concern because exposure to environmental toxicants negatively affect health, which can impair academic success. To date, it is unknown if associations between air toxics and academic performance found in previous school-level studies persist when studying individual children. In pairing the National Air Toxics Assessment (NATA) risk estimates for respiratory and diesel particulate matter risk disaggregated by source, with individual-level data collected through a mail survey, this paper examines the effects of exposure to residential environmental toxics on academic performance for individual children for the first time and adjusts for school-level effects using generalized estimating equations. We find that higher levels of residential air toxics, especially those from non-road mobile sources, are statistically significantly associated with lower grade point averages among fourth and fifth grade school children in El Paso (Texas, USA).

Keywords

Environmental justice; children; academic performance; National Air Toxics Assessment; El Paso; Texas; USA

1. Introduction

Children are more physiologically vulnerable to the effects of air pollution than are adults (Brugha and Grigg 2014; Bertoldi et al. 2014) and exposure to environmental toxicants can harm their rapidly developing respiratory and neurological systems (Guxyens and Sunyer 2012). Children spend more time outdoors than do adults, e.g., playing outside after school,

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and thus face greater exposure to air pollution. As environmental justice studies have demonstrated, in some urban contexts, neighborhoods with higher proportions of children are disproportionately exposed to greater levels of environmental toxicants (Gordon and Dorling 2003; Basile et al. 2006; Grineski and Collins 2008). For these reasons, environmental justice (EJ) researchers are concerned about exposure to air pollution resulting in worse school performance for children (Pastor et al. 2004; 2006; Mohai et al. 2011). Children are a focal group in EJ research because they are more likely to experience economic deprivation than are adults; they have little to no say in where they live or attend school and struggle to protect themselves from the negative impacts of air pollution; and they may face deleterious health outcomes due to the lifelong consequences of disproportionate early life exposure.

This concern for children stems from a broader set of EJ analyses in the US that have shown that environmental risks have disproportionately fallen on minorities and the poor; multiple studies have found that race and class are the greatest predictors of exposure to environmental hazards in the US (Morello-Frosch et al. 2011; Mohai et al. 2009; Brulle and Pellow, 2006; Brown 1995; Mohai et al. 2009a). Contemporary associations between race, class and environmental disadvantage trace their roots to historical patterns of *de jure* and *de facto* spatial segregation and the lack of political clout in poor and minority communities (Mohai et al. 2009a). The US federal government has recognized the presence of environmental injustices as an important domestic issue and as such, the Environmental Protection Agency (EPA) has defined Environmental Justice as,

The fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies. Fair treatment means that no population, due to policy or economic disempowerment, is forced to bear a disproportionate share of the negative human health or environmental impacts of pollution or environmental consequences resulting from industrial, municipal, and commercial operations or the execution of federal, state, local and tribal programs and policies (US Institute of Medicine, 1999, pg. 1).

Building from studies of school-based environmental injustice (Chakraborty and Zandbergen 2007), a handful of studies in US cities and states have examined associations between levels of air pollution, measured in a variety of ways, and student academic performance outcomes at the level of the school. They have tended to find associations between greater exposure to air pollution and worse student performance. One of the first studies to do so measured the association between US Toxic Release Inventory (TRI) data and 1990 census tract-level estimates of respiratory air toxics risk and aggregated standardized test scores for schools in the Los Angeles Unified School District (California, USA) (Pastor et al. 2004). Using ordinary least squares (OLS) regression models, Pastor et al. (2004) found that air pollution risks were negatively and statistically significant correlates of test scores adjusting for school demographics. Expanding to include all public schools in California, Pastor et al. (2006) found that the general pattern observed in Los Angeles held for the rest of the state.

Outside of California, similar studies have been conducted in Baton Rouge, Louisiana, USA (Lucier et al. 2011; Scharber et al. 2013). A school's proximity to a TRI facility (measured six different ways) was significantly and negatively associated with lower aggregate standardized test scores, controlling for a host of relevant school-level covariates (Lucier et al. 2011). Scharber et al. (2013) compared associations between chemicals released by TRI facilities that are specifically known to impact children's development and standardized tests scores. They found that when they included only known or suspected developmental, neurological and respiratory toxicants in their OLS models (as opposed to using Lucier et al's (2011) more general toxicity variable), their coefficient estimates became larger and more statistically significant (Scharber et al. 2013).

In addition to standardized test score outcomes, school absenteeism has been studied in relationship to air pollution exposure. Mohai et al. (2011) found that schools in the highest decile for pollution in the state of Michigan (USA), measured using TRI-derived Risk-Screening Environmental Indicators (RSEI) provided by the United States Environmental Protection Agency (USEPA), had significantly higher levels of absenteeism (and lower standardized test scores), controlling for a host of school-level factors. Studying the state of Texas (USA) due to its substantial spatial variability in air pollution, Currie et al. (2009) employed panel data for 1,512 schools (not students) within the state's 39 largest school districts and found higher levels of absenteeism associated with greater school-based exposure to criteria pollution.

In terms of understanding the mechanisms behind the link between air toxic exposures and children's academic performance found in previous studies, there are two hypothesized pathways. First, exposure to air pollution puts children at greater risk for respiratory infections and asthma (Ostro et al. 2009; Belleudi et al. 2010; Grineski et al. 2010). Being ill causes children to miss school, which negatively impacts their learning, grades, and standardized test scores (Pastor et al. 2004; Pastor et al. 2006; Currie et al. 2009). Second, when children are chronically exposed to air toxics, their cognitive and neurological development may be delayed or impaired and they may have lower grades and standardized test scores because of it (Guxens and Sunyer 2012).

Making four methodological improvements on previous EJ studies (Pastor et al. 2004; Pastor et al. 2006; Lucier et al. 2011; Scharber et al. 2013; Mohai et al. 2011; Currie et al. 2009), we examine associations between air toxics risk estimates from multiple pollutant sources and grade point averages among a representative, population-based sample of 4th and 5th graders in El Paso, Texas, USA. First, we rely on student-level data collected through a mail survey to study individual children, rather than schools. Given the ecological fallacy, one cannot assume that the association found at the level of the school exists at the level of the individual. Second, the use of primary survey data enables us to use individual students' grade point average (GPA) instead of standardized test scores aggregated at the level of the school. Third, we employ an array of air toxics indicators using the USEPA's National Air Toxics Assessment (NATA), which are assigned to the child's home address, where he/she hypothetically spends the most hours each day. Unlike Pastor et al. (2006), we include diesel particulate matter (PM), in addition to respiratory risk, and disaggregate both by source (i.e., point, on-road mobile, non-road mobile and non-point sources) to capture a

variety of risk indicators. While not examined as a correlate of academic performance before, environmental injustices in exposure to diesel PM have been noted (Su et al. 2012), and diesel exposure has been associated with health effects in children (Roberts et al. 2013; Habre et al. 2014). Fourth, we use generalized estimating equations (GEE), because they accommodate analyses of non-normally distributed and clustered data (Liang and Zeger 1986; Zeger and Liang 1986; Diggle et al. 1994). In this case, GEEs allow us to adjust for clustering by school and thus isolate the individual-level effects of the residential air toxics risk indicators examined. GEE is the best choice for this analysis because not accounting for clustering by school would violate assumptions of OLS models and yield parameter estimates biased by school-level effects.

2. Materials and Methods

2.1 Study context

The study took place in El Paso, Texas, USA. El Paso is located on the US-Mexico border and the city has an estimated population of 640,066 (as of 2011) (American Community Survey 2011). The 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%). El Paso is also home to a bilingual populace. As of 2011, 26% of residents speak English only, while 72% speak Spanish; among Spanish speakers, 27% are not English proficient. Among El Paso residents, 26% are foreign-born, and 15% are not US citizens.

Air quality is a serious concern in El Paso. El Paso, along with Laredo and Houston, are rated highest for carbon monoxide levels in Texas (Currie et al. 2009). El Paso is ranked eighth out of 277 metropolitan areas in the US for annual particulate pollution (American Lung Association 2014). Collins et al. (2011) found that the cumulative lifetime cancer risk from all toxic emission sources in El Paso County was greater than 30 per million and that the block group with the lowest cumulative cancer risk estimate was still 20 times higher than the threshold set by the 1990 Clean Air Act Amendment.

More specifically, El Paso is home to many large-scale polluting facilities, thriving trucking and rail freight industries and an expanding military base. Key point sources of pollution include Western Refining, Phelps Dodge Copper Products, and those associated with Fort Bliss and its US Army Air Defense Artillery Center (USA Today 2009). The trucking industry is a critical contributor to transportation-related on-road mobile air toxics in El Paso. After the North American Free Trade Agreement (NAFTA) was enacted in 1994, trucking became a major source of air pollution along the US-Mexico border. In one year, nearly 400,000 trucks crossed from Ciudad Juárez (Mexico) through El Paso's Ysleta-Zaragoza Port of Entry alone and another 360,000 trucks crossed through El Paso's Bridge of the Americas Port of Entry (US Customs and Border Protection 2014), transporting manufactured goods produced in Ciudad Juárez's *maquiladora* industry.

El Paso is also home to three substantial non-road mobile sources of pollution: the El Paso International Airport, Fort Bliss, which includes the US Army Air Defense Artillery Center,

and a system of railways for transporting freight. The El Paso Airport had over 90,000 aircraft operations in 2013 (El Paso International Airport 2013). Fort Bliss is the second largest military base in the US and it has 1,500 square miles of restricted air space that is used for missile testing and artillery training. El Paso is also a crossover station for east-west rail freight within the US and international rail traffic from Mexico; it is home to rail yards and intermodal terminal facilities as well (Texas Department of Transportation 2011).

2.2 Data collection

Socio-demographic and academic performance data were collected through a cross-sectional mail survey that was sent to all caretakers of fourth and fifth grade student enrollees in the El Paso Independent School District in 2012 (Grineski et al. 2014). The El Paso Independent School District (EPISD) is the 10th largest district in Texas and the 61st largest district in the United States. In 2012, there were over 64,000 students (K-12) enrolled in 94 campuses.

We used the Tailored Design Method to obtain the highest response rate possible (Dillman et al. 2009). First, we sent out a survey package that consisted of a consent form, English and Spanish versions of the survey, 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 survey package to all non-respondents. A total of 6,295 surveys were delivered to the caretakers 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 (Curtin et al. 2000; Holbrook et al. 2008; Keeter et al. 2006; Visser et al. 1996). For example, a meta-analysis found that response rates poorly predicted nonresponse bias (Groves and Peytcheva 2008). Our sample was generally representative of the demographics of EPISD fourth and fifth graders in terms of ethnicity. The percent Hispanic in our sample was 82.2% versus 82.6% for all EPISD fourth and fifth graders. The sample was slightly less poor as the percent of students qualifying for free or reduced price meals was 60.0% in our sample vs. 71.3% among all fourth and fifth graders.

Information was gathered through the survey on both the primary and secondary caretakers of the child. Primary caretakers were 83% mothers; 10% were fathers, 4% were grandparents, 1% were step-parents, and another 1% were aunts/uncles. Secondary caretakers were 57% fathers; 13% were mothers, 8% were grandparents, 10% were step-parents, and 1% were aunts/uncles. We drew from questions asked about the primary and secondary caretaker to create variables applicable to the child's mother for the analysis.

Six children were excluded from this analysis because they lived outside of the county limits. Two students were excluded because they attended an alternative school and another was excluded because the child who had been enrolled in a school at the time of the mailing was being home-schooled at the time of the survey. Given that our statistical modeling accounts for clustering at the level of the school (see below), it was not appropriate to retain any child who was the only student from a given school. Thus, we analyzed data on 1,895 children.

2.3 Variables

2.3.1 Children's academic performance—Grade Point Average (GPA) was calculated using caretaker-reported grades from the survey. The caretaker was asked “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. The list of subjects and response options are a perfect match with official EPISD report cards. 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 dependent variable. Descriptive statistics are presented in Table 1. On average, children did well in school as the mean GPA was 3.3 out of 4.0. This grade distribution follows the national pattern for grades received in elementary school. According to U.S. Department of Education (2009) data, 82.2% of students received both either mostly A's or mostly B's nationwide in 2007. While not a perfect comparison, 78.4% of children in our sample had GPAs above 3.0.

2.3.2 Air toxics variables—We used the USEPA's 2005 National Air Toxics Assessment (NATA) census block-level database to create the child-level pollution values used in the analysis. The NATA includes all air toxics 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 2013b). NATA is currently the best available secondary data source for spatially explicit characterization of air toxics exposure risk in US metropolitan areas (Roberts et al. 2013; Linder et al. 2008; McCarthy et al. 2009; Su et al. 2009; Marshall et al. 2014) and the 2005 NATA is the most recent version available. The USEPA works with states and industries to gather data about air toxics emissions and then compiles them in the NATA. The methodology used assumes that the risks of different pollutants are additive and can be summed to estimate an aggregate risk score for each geographic unit.

To generate the estimates for the 2005 NATA respiratory and diesel PM risk data, the EPA first uses the data from the National Emissions Inventory (NEI) and inputs it into the a Gaussian Dispersion model, also known as the Assessment System of Population Exposure Nationwide (ASPEN), which controls for atmospheric events such as wind and temperature (Chakraborty 2009). Next, these ASPEN estimates are put into an inhalation exposure model known as the Hazardous Exposure Air Pollution Exposure Model 5 (HAPEM5), which is designed to estimate inhalation exposure for specified air toxics. Through a series of calculations, the HAPEM5 model arrives at inhalation exposure estimates using data on census-derived age and sex cohorts, assumptions about age- and sex-based human activity patterns, ambient air quality levels, meteorological information, and indoor/outdoor concentration relationships (Environmental Protection Agency 2011). From these exposure concentrations, the NATA estimates public health risks from inhalation of air toxics following the EPA's risk characterization guidelines, which assume a lifelong exposure to 2005 levels of outdoor air emissions (Grineski et al. 2013).

Dose-response relationships for respiratory and diesel PM risk are expressed in terms of the inhalation reference concentration (RfC) for each pollutant. RfC is defined as the amount of

toxicant below which long-term exposure to the general population of humans is not expected to result in any adverse effects (Pastor et al. 2006). To estimate respiratory and diesel PM risk, the EPA uses the RfC as part of a calculation called the hazard quotient—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 calculated using the hazard index (HI), defined as the sum of hazard quotients for individual air toxics 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 cause irritation by different (i.e., non-additive) mechanisms. Although the HI cannot be translated to a probability that adverse effects will occur, a HI greater than 1.0 indicates the potential for adverse effects (Environmental Protection Agency 2011a). Unfortunately, the EPA does not yet have sufficient data to assign a numerical carcinogenic potency for diesel PM, so the health effects included in the calculations are non-carcinogenic (Environmental Protection Agency 2014). 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, which assumes that one out of one million people would develop cancer throughout their lifetimes, given they that were exposed continuously, in addition to those who would develop cancer otherwise within the population (Environmental Protection Agency 2011a)

Respiratory and diesel particulate matter risk estimates are broken out by pollutant source. We use (1) *total respiratory risk*, which is the summation of all respiratory risk pollutant source variables in the NATA including background and secondary source risk estimates; (2) *on-road mobile respiratory risk*, which includes emissions from vehicles found on roads and highways such as cars, trucks, and buses; (3) *point* (formerly called “major”) *respiratory risk*, which includes emissions from factories, refineries, and power plants; (4) *non-road mobile respiratory risk*, which includes emissions from mobile sources not found on road and highways e.g., airplanes, trains, and construction vehicles; and (5) *non-point* (formerly called “area”) *respiratory risk*, which includes emissions from smaller scale activities than those captured in the point estimates, e.g., small polluting facilities such as dry cleaners and fast food restaurants (Environmental Protection Agency 2013). Additionally, we include diesel variables, although they are limited and only include (6) *total diesel particulate matter (PM)*, (7) *on-road diesel PM* and (8) *non-road diesel PM*. We assigned the 8 NATA values to each child based on the block-level NATA estimates for the census block in which the child's home address was located (Roberts et al. 2013). These block level estimates, which we received directly from the USEPA, are at a finer spatial resolution than the publically available census tract estimates used to assign risk values to children's home addresses in other studies (Roberts et al. 2013; Lupo et al. 2011). The USEPA weights the block level values based on population in order to create the publically available census tract-level values, published on the USEPA's website. Descriptive statistics for these variables are presented in Table 1 and standardized versions of all NATA variables are used in the models.

2.3.3 Control variables—We adjust for eight individual-level control variables based on a review of the children's academic performance literature. Economic deprivation has been linked to decreased academic performance (Reardon and Galindo 2009) and is represented

here by the (1) child qualifying for free or reduced price meals at school (FRPM). FRPM, which is 185% of the federal poverty line, is a less conservative measure of economic deprivation than is poverty; this is important as many families living above the poverty line still face economic hardship (Brady, 2003). Guidelines for constructing this variable were obtained from the US Food and Nutrition Service of US Department of Agriculture and we used the two following survey questions in our calculations: 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)?” The variable was then coded as 0=not qualifying for free or reduced price meals and 1=qualifying for free or reduced price meals. In total, 60% percent of participating students qualified for free or reduced price meals.

We control for (2) mother's education (measured as years of schooling completed) because children with well-educated mothers tend to perform better in school than do those with less educated mothers (Magnuson 2007). Mothers had about 13 years of education on average, which equates to just over a high school diploma. We adjust for (3) the mother being a teenager at birth of the child because children born to teen mothers tend to fare worse in school as it is more challenging for these mothers to provide educationally stimulating home environments (Magnuson 2007). Our continuous mother's age at the birth of her child variable was dichotomized into 1=teenage mother (19 and younger) and 0=not a teenage mother (20 years and older). Approximately 9% of children had a teenage mother at the time of their birth.

We control for race/ethnicity because having a (4) black/African American and/or (5) Hispanic mother has been associated with lower levels of academic performance among children. The achievement gap between students of color and white students has been well documented (Reardon and Galindo 2009; Kao and Thompson 2003; Duncan and Magnuson 2005; Bali and Alvarez 2003) and likely stems from multiple social factors including institutional racism and discrimination against poor and minority students, the underfunding of public schools especially in poverty stricken neighborhoods, school tracking, and family structure (Duncan and Magnuson 2005; Kao and Thompson 2003; Fisher et al. 2000). To determine the mother's race/ethnicity, we drew from two questions that asked, “Are you of Hispanic, Latino, or Spanish origin?” and “What is your race?” to create two mutually exclusive variables: Hispanic (0=no; 1=yes) and non-Hispanic black (0=no; 1=yes). 80% of mothers were Hispanic while another 2% were non-Hispanic black.

We adjust for (6) mother's English proficiency because mothers in the US 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). Mother's English proficiency was measured using the question: “How well do you speak English?” with the possible answers being 0=not at all; 1=not well; 2=well; and 3=very well. This variable is treated as a continuous indicator; mothers had an average score of 2.17. We also adjust for (7) children's current age (in years) and (8) sex of the child (0=female; 1=male). Because the survey only targeted fourth and fifth grade children, the average age of the child is 10; the youngest child was 8 and the oldest was 13. Both males and females are equally represented in the sample.

2.3.4 School—We control for clustering at the level of the school since the school is a known influence on children's academic performance (Mohai et al. 2011). The generalized estimating equations (GEEs) estimated statistically account for school-level effects as a nuisance parameter, enabling us to isolate the effects of the individual-level residential air toxics risk variables, as well as the individual-level controls, on the academic performance of children. Each child was assigned a numeric categorical value corresponding with their elementary school (1-58). The minimum number of children attendees by school was 8, while the maximum was 61.

2.4 Methods

Data were multiply imputed using IBM SPSS version 20 to address non-response bias. Multiple imputation (MI) is currently the best method to address missing data in quantitative analysis and is used to avoid bias that may occur when values are not missing completely at random (Penn 2007). We imputed missing values for 20 datasets to increase power using a regression-based approach, and we specified 200 between-imputation iterations to ensure independence among the datasets (Enders 2010). Using 20 data sets is the current “rule of thumb” in MI as it maximizes power (as opposed to using 3–5 data sets, which used to be the convention) and improves the validity of multi-parameter significance tests (Enders 2010). Analyzing a single imputed data set would effectively treat the filled-in values as real data, so even the best imputation technique, when used with just one imputed data set may underestimate sampling error. MI techniques appropriately adjust the standard errors for missing data (Enders 2010). We included all relevant variables in the multiple imputation procedure. The percent missing for the variables ranged from 1.7% to 14.0% (see Table 1).

Multiply imputed data were first used with SPSS version 20 software to calculate bivariate correlations. Then, multiply imputed data analyses were performed using generalized estimating equations (GEEs) with robust (i.e., Huber/White, sandwich, empirical) covariance estimates. GEEs extend the generalized linear model (Nelder and Wedderburn 1972) to accommodate correlated data. GEEs provide a general method for the analyses of clustered continuous, ordinal, dichotomous, polychotomous and event-count response variables, and relax several assumptions of traditional regression models. For our purposes, GEEs enable us to examine the association between air toxics and GPA in reference to a non-normally distributed dependent variable, and while accounting for school effects.

In this case, GEEs are preferable to other modeling approaches that account for non-independence of data (e.g., mixed models with random effects or fixed effects models). This is because GEEs estimate unbiased population-averaged (i.e., marginal) regression coefficients even with misspecification of the correlation structure when using a robust variance estimator (Liang and Zeger 1986; Zeger and Liang 1986). Mixed models with random effects, in contrast, generate cluster-specific (i.e., conditional, subject-specific) results, which would not elucidate average responses over the population (Diggle et al. 2002). Additionally, because our focus is on population-averaged predictors of GPA, and not school effects, GEEs are appropriate because the intracluster correlation estimates are adjusted for as nuisance parameters and not modeled as in multilevel modeling approaches (Diez Roux 2002). Additionally, GEEs relax assumptions of random and fixed effects

models that our data violated; the capacity of GEEs to accommodate both non-normally and clustered data while handling unmeasured dependence between outcomes offered key advantages (Liang and Zeger 1986; Zeger and Liang 1986; Diggle et al. 1994). Although other methodological approaches may account for the intracluster correlation, especially when the dependent variable is normally distributed, GEEs offered the additional advantage of not requiring the correct specification of the correlation matrix in order to reach unbiased statistical conclusions about the covariates' effects, given that the robust estimation of standard errors be applied (as is the case in our analysis). In this case, we specified the exchangeable correlation matrix, which assumes constant intracluster dependency (i.e., compound symmetry), so that all the off-diagonal elements of the correlation matrix are equal.

To select the best fitting model, we compared different choices for distribution, using the quasi-likelihood under independence criterion (QIC) as a measure of model fit (Garson 2012). Based on visual inspection of the histogram of our dependent variable, we ran gamma with log link, linear with log link, and Tweedie with log link. The gamma with log link had the lowest QIC for each of the eight models, so this specification was used. Each model analyzes the effects of exposure to one of the air toxics variables on GPA, adjusting for the eight control variables. We could not include multiple air pollution variables together in any single model due to concerns about collinearity. Due to the exploratory (as opposed to confirmatory) nature of the analysis, we did not correct for multiple comparisons (Bender and Lange 2001) and employed two-tailed tests of significance.

3. Results

3.1 Correlations

Correlations are presented in Table 2. All eight NATA variables were negatively ($r=-0.08$ to -0.21) and significantly ($p<.01$) correlated with lower GPAs; respiratory point risk had the weakest correlation of the eight. Qualifying for free or reduced priced meals ($r=-0.33$, $p<.01$) exhibited the strongest (negative) correlation with children's GPA. Mother's education ($r=0.31$, $p<.01$) exhibited the second strongest (positive) correlation with children's GPA. Mother being Hispanic, having a teen mother, being younger and being male were also associated ($p<.01$) with lower GPA.

3.2 GEE Results

For respiratory risk (see Table 3), all sources of respiratory risk except for point were statistically significant ($p<.05$) and negatively associated with GPA. For the significant risk estimates, the effect on GPA ranged from a decrease of 0.019 points (on-road) to a decrease 0.036 points (non-road). For every one standard deviation increase in non-road respiratory risk (the risk variable with the largest effect on GPA), the average student's GPA decreased by 0.036 points.

In terms of the findings for the diesel PM risk variables (see Table 4), all three risk variables were statistically significant ($p<.05$) and negatively associated with GPA. Non-road diesel PM had the strongest effect on GPA as a one standard deviation increase was linked to a

0.035 point decrease in GPA. On-road diesel PM had the weakest effect on GPA of the three risk variables examined as a one standard deviation increase was associated with a 0.018 point decrease in GPA. In terms of the control variables (see Tables 3-4), being male ($p < .01$), qualifying for free and reduced price meals ($p < .05$) and having a mother with lower levels of education ($p < .01$) were statistically significantly associated with a lower GPA. The other five control variables were not significant.

3.3 Limitations

First, this study examined the impacts of exposure to air toxics on children's academic performance at the individual level adjusting for school effects at one point in time. The cross-sectional nature of the approach make it impossible to separate the relationships between hazardous air pollutants and potentially contemporaneous cofounders. Longitudinal data would have supported stronger inferences than the cross-sectional approach implemented here, and future studies should employ longitudinal designs. To date, only one study on this topic has employed longitudinal methods (Currie et al. 2009). Second, due to grade inflation (a national trend also occurring in El Paso), the majority of children have high GPAs, which limits the variability of our dependent variable. Third, while our sample was representative of 4th and 5th graders in EPISD in terms of ethnicity, the 30% response rate may be improved upon through the use of multimode data collection designs. The survey respondents did experience less economic deprivation than all fourth and fifth graders enrolled in EPISD in 2012 (i.e., 60% qualifying for FRPM vs. 71%). If we are underestimating the level of economic deprivation in the EPISD then we may be underestimating relationships between air toxics exposure and academic achievement.

Fourth, there are limitations associated with using USEPA NATA data. We were forced to pair the 2005 estimates, which are the most recent available, 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 only on inhalation exposure from air toxics, which neglects exposure through other pathways like skin contact or ingestion. It also does not include criteria pollutants, which are an important source of risk. The risk calculations do incorporate demographic data (i.e., age groups and sex) from the US census (Environmental Protection Agency, 2011), which could confound associations between air toxics risk and outcome variables in any EJ study, including this one. While the census block level NATA cancer risk estimates used here provide more locational precision than has been achieved in previous individual-level studies employing census tract-level NATA data (Lupo et al. 2011; Roberts et al. 2013), they still are not perfectly suited for individual-level exposure assessment. Better fine-scale exposure assessment methods exist, but they are time and resource intensive, and thus impracticable (i.e., cost-prohibitive) for characterizing fine-scale exposure risks the level of an entire metropolitan area. Lastly while this study contributes to the literature on air toxics and children's academic performance in the US, future studies should examine non-US contexts to provide a more well-rounded examination of this important topic, which has rarely been studied outside of the US.

4. Discussion

These individual-level findings corroborate previous research linking school-based air pollution exposure to school-level academic performance outcomes (Pastor et al. 2006; Lucier et al. 2011; Mohai et al. 2011). Our results support somewhat more definitive conclusions about the risks of air toxics on children's school performance than was possible based on the previously completed ecological school-level studies. They underscore the continuing need to emphasize children as a vulnerable population in EJ research and activism (Mohai et al. 2011).

This study demonstrates that seven of the eight NATA risk variables were significantly and negatively associated with child's GPA in the GEEs (with the effect size ranging from -0.018 to -0.036). The coefficient for the point source respiratory risk was not significant in the multivariate model, although it was significant in the bivariate correlations. The fact that all but one air toxics variables remained significant even when controlling for parental, socio-demographic and school-level effects may indicate that residential exposure to air pollution has an independent effect on children's academic performance that cannot be dismissed with explanations of economic deprivation, maternal English language deficiencies, low educational attainment, nor school-level institutional or environmental factors at which were controlled for by design in the GEE models.

This study also addresses a limitation in the school-level literature on air pollution/academic performance by moving beyond the implicit assumption that school-site exposure is the primary pathway through which air toxics exposures impact student academic performance. We examined residential exposure because children (theoretically) spend more time at home than at school, and because it has not been investigated in any previously published study. Additionally, our findings provide support for existence of an air pollution-school performance relationship, since we examined GPA as an outcome; previous studies have found similar patterns at an aggregate level by examining only school-averaged standardized test scores and absenteeism (Mohai et al. 2011).

When comparing the strength of association between air toxics and GPA in the GEEs, non-road respiratory risk had the strongest relationship with GPA of the eight toxics variables tested, followed closely with by non-road diesel PM. Previous studies have demonstrated the importance of respiratory risk estimates on test scores at the level of the school (Pastor et al. 2006) but have not disaggregated them by source. Mobile sources of air toxics contribute substantially to the respiratory risk burden in El Paso. Considering point, non-point, on-road, and non-road sources of respiratory risk in the 2005 NATA, 85% of the respiratory risk burden in El Paso County came from mobile sources (with 20% from non-road mobile sources); only 15% came from point and non-point sources. It may be that exposure to non-road mobile air toxics, such as those produced by El Paso's airport, military base, and railways, is linked to reduced GPA through its association with serious respiratory infections and school absenteeism. In El Paso, non-road mobile respiratory risk (from the 1999 NATA) was the strongest predictor of children's hospitalization rates from respiratory infections ($p < .05$) as compared to the other NATA respiratory risk sources (Grineski et al. 2013).

In terms of which pollutant sources presented the greatest risks to children's academic performance, the non-road mobile sources had the largest effect on GPA across both respiratory and diesel PM risk models, which suggests that children's exposure to pollution from airplanes, construction vehicles, and trains may be more detrimental than has previously been recognized. It is unknown if this finding is unique to El Paso, or applicable to other contexts as previous studies have not disaggregated NATA estimates by source, as we do here. Although El Paso is home to multiple sources of non-road pollution, these findings may be also generalizable to other metropolitan areas. While point (e.g., factories) and on-road mobile (e.g., freeways) sources of air pollution have received the most attention in the policy and academic arenas, the contribution of non-road mobile sources to the overall pollution burden is increasingly being recognized nationwide. For example, new evidence suggests that the particle pollution generated from the Los Angeles International airport extends over 10 kilometers and is of the same general magnitude as the entire freeway system in Los Angeles, California, USA (Hudda et al. 2014). These findings suggest that future work must take seriously the impacts of non-road mobile sources of air pollution, like airports and military activities involving airplanes.

5. Conclusion

While previous studies of air pollution-academic performance relationships using NATA have focused on respiratory risk (Pastor et al. 2006), they have not disaggregated toxicants by source and our analysis illustrates the utility of doing so. These findings suggest which pollutant sources which may have the greatest impact on children's academic performance, which can inform further research and policy aimed at reducing the most harmful toxic emissions. Whereas previous studies have largely been concerned with point sources of pollution, our findings show that the risks of air toxics have multifaceted origins. To our knowledge, our documentation of the impact of non-road mobile air toxics on reduced academic performance in El Paso is novel.

While our results suggest relatively small statistical effects of air toxics on GPA, those effects are robust, since they are stable across multiple models and in the presence of a suite of covariates that are known determinants of children's GPA. So, air toxics exposures may not dramatically effect children's school performance at a population level, but results suggests that there are significant mild impacts that are probably impossible in typical cases to recognize at the level of an individual child's development and performance in school. Thus, effects appear to be insidious, since they are mild, unlikely to be perceived, and, hence, unlikely to be addressed in any way. It would be important to note that seemingly trivial effects on children's development may translate into substantial impacts throughout the life course, in terms of physical and mental health and personal success (e.g., lifetime earnings).

Poor academic performance at a young age can have lifelong impacts on a person's developmental trajectory and life chances, including lower economic and educational attainment in adulthood. Among children with chronic health conditions, lower GPAs and standardized test scores have been linked to worse labor market outcomes and poorer health in adulthood (Case et al. 2005). Children's academic achievement before the eighth grade

has a greater impact on college preparedness than any learning that happens during high school (ACT, 2008). While exposure to air toxics is worrisome for adults, the repercussions of chronic exposure is most dire for children because they are physiologically vulnerable in terms of their growth and development (Brugha and Grigg 2014; Bertoldi et al. 2012) and because negative impacts on their academic performance may have lifelong impacts, which in turn affects the social reproduction of economic deprivation (Perera 2008). The impact of air toxics on academic performance may be yet another disadvantage that is disproportionately borne by low-income children, who are also likely to face exposure to crime and other social risks, and have reduced access to resources that could decrease the effects of exposure to air pollution (e.g., access to healthcare, medications and air purifiers).

In El Paso, we believe that exposure to air toxics likely compounds the learning challenges faced by the average student, who comes from a low-income, limited English background and may already be struggling in school. This likely creates a situation of ‘multiple jeopardy’ (Institute of Medicine Committee on Environmental Justice, 1999) for many El Paso youth. The reduced GPA among children exposed to air toxics is a disadvantage that contributes to an uneven playing field, which further decreases these children's life chances, compared to their economically-advantaged counterparts.

In sum, the finding that there is a significant association between residential exposure to air toxics and GPA at the individual level is both novel and disturbing. We demonstrate that, even after controlling for economic, demographic and school effects, exposure to residential air toxics has a negative impact on children's GPAs. While El Paso is socio-demographically unique, it reflects how other US cities will begin to look in the coming decades as the Hispanic population continues to grow nationwide. The results of this study also contribute to a broader demographic understanding of the impacts of air toxics exposures on school performance because the relationship between air toxics and school performance also exists in the case of a predominantly Hispanic population, in reference to outdoor exposures at home sites (instead of at schools), and at the individual level. It is also the case that the findings reported here corroborate previous studies done in other geographic areas (Pastor et al. 2006; Scharber et al. 2013), suggesting that it is not local demographics driving the findings, but an underlying association between air toxics and academic achievement. These findings provide another piece of evidence that should inform advocacy for pollution reduction in the US and beyond.

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Table 1

Descriptive statistics for GPA, respiratory and diesel PM NATA air toxics risk estimates by source, and control variables

CONTINUOUS VARIABLES	N	Min	Max	Mean	SD	% Missing
GPA	1690	0.2	4	3.3	0.01	10.8
Total Respiratory	1895	.60	6.88	1.9424	.86620	0
Point Respiratory	1895	.1425	2	2.6128	2.0501	0
On-Road Mobile Respiratory	1895	.05	5.39	.7352	.68298	0
Non-Road Mobile Respiratory	1895	.01	.61	.1837	.10419	0
Non-Point Respiratory	1895	.01	.61	.1609	.100345	0
Total Diesel Particulate Matter	1895	.12	7.93	1.3165	1.06256	0
On-Road Diesel PM	1895	.07	7.49	1.0037	9.4924	0
Non-Road Diesel PM	1895	.04	1.24	.3078	.18453	0
Child's age	1862	8	13	10.4	0.8	1.7
Mother's education	1692	1	21	13.06	3.9	10.7
Mother's English proficiency	1655	0	3	2.2	1.0	12.7

DICHOTOMOUS VARIABLES	N	Yes	No	% Missing
Child is male	1835	916	919	3.2
Free/reduced priced meals	1656	1001	665	12.6
Teenage motherhood	1633	142	1488	14
Mother is Hispanic	1672	1344	328	11.8
Mother is non-Hispanic black	1700	41	1659	10.3

Table 2

Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. GPA																
2. Total Respiratory	**															
3. Point Respiratory	-.203	**														
4. On Road Mobile Respiratory	-.089	**	.083													
5. Non Road Mobile Respiratory	-.183	**	.968	.046												
6. Non Point Mobile Respiratory	-.206	**	.759	.011	.599											
7. Total Diesel PM	-.197	**	.740	.062	.571	.901										
8. On Road Diesel PM	-.195	**	.985	.036	.990	.644	.698									
9. Non Road Diesel PM	-.181	**	.967	.046	1.000	.567	.594	.990								
10. Child is male	-.198	**	.700	-.031	.558	.797	.667	.553								
11. Child's age	-.085	**	-.004	.000	-.028	-.027	-.004	.001	-.030							
12. Free or reduced prices meals	-.078	**	.038	.024	.075	.082	.033	.023	.072	.018						
13. Teenage motherhood	-.327	**	.341	.111	.325	.340	.334	.315	.309	.033	.090					
14. Mother's education	-.117	**	.067	.077	.055	.076	.060	.059	.044	.033	.053	.129				
15. Mother is Hispanic	.305	**	-.321	-.292	-.324	-.319	-.312	-.288	-.320	.026	-.102	-.487	-.090			
16. Mother is non-Hispanic black	-.202	**	.247	-.035	.265	.275	.237	.217	.248	-.026	.032	.327	.072	.269		
17. Mother's English proficiency	.009	**	-.068	.086	-.077	-.071	-.069	-.062	-.077	.051	.020	-.067	.020	.075	.321	
	-.051	*	.105	.011	.098	.119	.093	.088	.080	-.028	.044	.126	.016	-.048	.304	-.076

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Table 3

Results of the Respiratory Risk GEE Models Predicting Child's GPA

Air toxic respiratory risk variable included in the model:	Model 1		Model 2		Model 3		Model 4		Model 5	
	Total ^a		Point ^a		On-Road ^a		Non-Road ^a		Non-Point ^a	
	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig
Child is male	-.032	.009	-.031	.011	-.032	.009	-.034	.006	-.033	.006
Child's age	-.012	.105	-.012	.106	-.012	.102	-.010	.142	-.011	.139
Free/reduced price meals	-.072	.023	-.079	.013	-.074	.020	-.071	.021	-.072	.021
Teenage motherhood	-.031	.299	.030	.314	.031	.292	.031	.294	.030	.319
Mother's education	.054	.000	.056	.000	.055	.000	.053	.000	.054	.000
Mother is Hispanic	-.047	.112	-.054	.069	-.049	.097	-.042	.150	-.045	.131
Mother is non-Hispanic black	-.095	.117	-.095	.124	-.096	.116	-.096	.112	-.096	.114
Mother's English proficiency	.017	.049	.017	.048	.017	.051	.017	.047	.018	.046
Air toxics risk ^a	-.026	.004	-.010	.295	-.019	.020	-.036	.001	-.028	.019

^aVariable was standardized before being entered into the model

Table 4

Results of the Diesel PM Risk GEE Models Predicting Child's GPA

	Model 6		Model 7		Model 8	
Air toxic diesel PM risk variable included in the model:	Total ^a		On-Road ^a		Non-Road ^a	
	B	Sig.	B	Sig.	B	Sig.
Child is male	-.032	.009	-.032	.009	-.034	.006
Child's age	-.012	.104	-.012	.102	-.010	.140
Free/reduced price meals	-.073	.021	-.075	.020	-.073	.018
Teenage motherhood	.031	.291	.031	.292	.032	.248
Mother's education	.054	.000	.055	.000	.052	.000
Mother is Hispanic	-.048	.105	-.049	.096	-.043	.140
Mother is non-Hispanic black	-.096	.116	-.096	.116	-.097	.111
Mother's English proficiency	.017	.051	.017	.051	.017	.051
Air toxics risk ^a	-.023	.008	-.018	.022	-.035	.000

^aVariable was standardized before being entered into the model