2015-01-01

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by

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THESIS

Presented to the Faculty of the Graduate School of

The University of Texas at El Paso

in Partial Fulfillment

of the Requirements

for the Degree of

MASTER OF ARTS

Department of Sociology and Anthropology

THE UNIVERSITY OF TEXAS AT EL PASO

May 2015

ACKNOWLEDGEMENTS

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 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, and Young-an Kim is gratefully recognized. This work was supported by Award Number P20 MD002287-05S1 from the National Institute of Minority Health and Health Disparities (NIMHD) and the Environmental Protection Agency (EPA). The content is solely the responsibility of the author and does not necessarily represent the official views of the NIMHD or EPA.

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CHAPTER ONE

INTRODUCTION

1.1 Background

The association between poor health and children's school performance has been well researched (Case et al. 2002; Forrest et al. 2012; Eide et al. 2009). When children have chronic health conditions they have more difficulty learning and retaining material than their healthy counterparts and have lower grade point averages and standardized test scores (Basch, 2011). Researchers have focused on specific health outcomes such as obesity, asthma, depression, and attention deficit hyperactivity disorder (ADHD), which have been shown to be negatively correlated with absenteeism (Pan et al. 2009; Silverstein et al, 2001) and academic achievement outcomes (Kramer et al. 1995; Forrest et al. 2012; Fowler et al. 1985; Eide et al. 2009; Currie and Stabile, 2005). Studies examining the association between children's general health status (which is often measured using a survey response option that ranges from "very poor" to "excellent") and academic achievement have found that poorer health is associated with worse school performance outcomes (Le at al. 2013; Spernak et al. 2006). Studies using both general health status and specific health outcomes have demonstrated similar results, which is that worse children's health status is linked to lower levels of academic achievement. The effect of poor health on children's academic achievement has long-term consequences on capital accumulation, labor outcomes, and life chances that reach into adulthood (Case et al. 2005; Palermo & Dowd, 2012).

A limitation of these studies is that they have not included the impacts of environmental toxins on children's academic performance, which have been shown to be significant influences according to the environmental justice literature (Pastor et al. 2004; Pastor et al. 2006; Mohai et al. 2011; Scharber et al. 2013; Lucier et al. 2011; Currie et al. 2009). Air toxics can put children at risk for respiratory illnesses, which causes them to miss school, which negatively impacts their learning, grades, and standardized test scores (Pastor et al. 2004; 2006). When children are continuously exposed to air toxics, their cognitive and neurological development may also be delayed or impaired and they may have lower grades and standardized test scores because of it (Guxens and Sunyer, 2012). The strength of the associations between air toxics and reduced school performance suggest that the impact of environmental toxins may account for the association between poor health and reduced school performance observed in other studies, although this has never been tested. It may also be the case that exposure to environmental toxins intensifies the association between poor health and school performance. But because the school health literature and the environmental justice literatures have remained largely separate, these hypotheses have yet to be investigated.

1.1.1 Environmental Justice

The Environmental Justice movement (EJ) is often traced back to Warren County, North Carolina. In 1973, a trucking company dumped 31,000 gallons of polychlorinated biphenyls (PCBs) along the roads in North Carolina and the state proposed to build a landfill to deal with the cleanup in the one of the poorest counties in the state. Residents of Warren County, a primarily black community, mobilized and eventually defeated the proposed bill that would have expanded the landfill, using tactics ranging from lawsuits to direct action (Szasz and Mueser, 1997). The events surrounding Warren County became highly publicized by the media and sparked the beginning of the Environmental Justice movement. After much deliberation, in 1999, the Environmental Protection Agency (EPA) 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). The term "environmental racism" sprang from the movement, attracting the attention of academics, which gave rise to the academic field of environmental sociology (Szasz and Mueser, 1997; Mohai et al. 2009).

The academic literature has shown that environmental risks in the US 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 1994). The majority of quantitative environmental justice studies have tended to use secondary spatial data such as census tract-level population variables and hazard data from the EPA's Toxic Release Inventory (TRI), which includes self-reported emissions from large point source polluters (Lucier et al. 2011; Legot et al. 2011). While important, a limitation of these studies has been that they are ecological in nature and subject to the ecological fallacy (Miao et al. 2015).

While the social science literature on environmental justice has shown that minorities and the poor are at higher risk for living near environmental hazards (e.g., Brulle and Pellow, 2006), few studies have actually been able to examine the concrete negative impacts (e.e., health impacts, like asthma attacks) stemming from living near environmental hazards. Unfortunately, it has been difficult to do so because of data limitations and methodological difficulties (Mohai et al. 2009a). Epidemiological studies, which are often done at the individual level, have been largely separate from environmental justice studies. The few environmental justice studies that have been able to look at the impacts of living near an environmental hazard have focused on health outcomes (Morello-Frosch et al. 2011; Downey and Willigen 2005; Vrijheid 2000). Instead, we focus on the impacts of environmental hazards on children's academic achievement, which is rarely often done (Pastor et al., 2004; 2006) but important. As such, this thesis draws builds on a long history of Environmental Justice activism and research.

1.2 Introduction to the Thesis

This thesis focuses on the association between exposure to air pollution and GPA, with a consideration of children's general health status. It addresses gaps in the literature because researchers have focused on the impacts of poor health and exposure to air toxins on children's academic achievement separately; none have looked at them together. The literature on air toxics and academic achievement has also been conducted at the school-level, whereas the analyses presented here are conducted at the individual-level. In this thesis, we examine how exposure to toxic air pollution impacts grade point average (GPA) in a sample of fourth and fifth grade children in El Paso, Texas.

This thesis is comprised up two papers. The first paper (Chapter 2) examines the impact of exposure to residential air toxins from a variety of sources on student GPA, while controlling for relevant covariates. The second paper (Chapter 3) adds the consideration of children's general health status and has multiple research questions. First, it tests whether poor health negatively impacts GPA, and as a second step, it incorporates air toxics variables into the models to test whether poor heath explains away the effect of exposure to air toxics on GPA. Lastly, it tests whether exposure to air toxics modifies the association between health status and academic achievement.

The study took place in El Paso, which is located on the US-Mexican border in Texas. As of 2011, El Paso has an estimated population of 640,066 and is the 19th largest city in the U.S. (US Bureau of the Census). The population is 81% Hispanic, compared to 17% of US population and 38% of the Texas population. About 14% of El Paso residents are non-Hispanic white, while 4% are non-Hispanic black.

Data for this project were collected through a mail-out survey that was sent to the primary caretakers of all fourth and fifth grade students enrolled in the El Paso Independent School District (EPISD) at the time of mailing. EPISD is the10th largest district in Texas and it is the 61st largest district in U.S. The EPISD survey was conducted in 2012 and pertained to respiratory health disparities; it was sent to 6,295 primary caretakers at their home addresses. Ultimately, 1,904 surveys were returned, for a 30% response rate. Data for the air toxics variables were obtained from the US Environmental Protection Agency's (EPA) 2005 National-Scale Air Toxics Assessment (NATA) census block-level database. The NATA dataset includes all hazardous air pollutants regulated by the Clean Air Act (except criteria pollutants) that are known or suspected to cause cancer or neurological, respiratory, immunological or reproductive diseases. All data for this thesis were multiply imputed using IBM SPSS version 20 to address non-response bias. SPSS was used to run bivariate correlations with multiply imputed data and generalized estimating equations (GEEs) were employed to answer the multivariate research questions, to be introduced next.

1.3 Research Questions and Hypotheses

Paper 1 (Chapter 2):

RQ1: Does residential exposure to air toxics significantly impact children's GPA, independent of individual-level factors?

We hypothesize that children who are exposed to higher levels of residential air pollution will have lower GPAs.

Paper 2 (Chapter 3):

RQ2: Does children's general health status, particularly poor health, negatively impact children's school performance outcomes, independent of relevant covariates?

We hypothesize that children who have lower general health status scores will have lower GPAs than their healthier peers.

RQ3: Does residential exposure to environmental toxins still significantly impact GPA, when accounting for children's health status?

We hypothesize that air toxins will be a significant predictor of GPA, but that they will not completely explain away the association between health status and air toxins.

RQ4: Does exposure to air toxics modify the association between children's health status and GPA?

We hypothesize that negative associations between health status and GPA will be stronger for students who have higher levels of residential exposures to air toxins.

1.4 Statement of Collaboration

As mentioned, this thesis is made up of two papers. The first is currently under review at a peer-reviewed academic journal, and the second paper is being formatted for submission to another peer-reviewed academic journal. While these papers were co-authored with my thesis advisor and committee, as the first author, I conducted the majority of research for the first paper (presented in Chapter Two) and the second paper (presented in Chapter Three) for the introduction, literature review, data analysis and writing. The co-authors provided guidance on proper statistical methods and revising the manuscripts.

Chapter 2: Clark-Reyna, S.E., Grineski, S.E., Collins, T.W. Residential Exposure to Air Toxics is Linked to Lower Grade Point Averages Among School Children in El Paso, Texas. Under review at *Population & Environment.*

Chapter 3: Clark-Reyna, S.E., Grineski, S.E., Collins, T.W. Childhood Health Status, Air Toxics, and Academic Achievement (being prepared for submission to *Journal of Community Health*).

1.5 Significance of the Study

The significant findings from my thesis are relevant to public policy in terms of the siting of schools and housing developments near polluting facilities, as well as other sources of air pollution such as airports and train yards. Findings stemming from this research can also be used to design school programs that improve children's health outcomes, and provide information to parents about the risks of exposure to air toxins. These implications are discussed in more detail later in the thesis.

CHAPTER 2

RESIDENTIAL EXPOSURE TO AIR TOXICS IS LINKED TO LOWER GRADE POINT AVERAGES AMONG SCHOOL CHILDREN IN EL PASO, TEXAS, USA

2.1. 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 toxins 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, 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 toxins (Gordon and Dorling 2003; Basile et al. 2006; Grineski and Collins 2008). For these reasons, environmental justice researchers are concerned about exposure to air pollution resulting in worse school performance for children, and ultimately reduced life chances because of it. Making methodological improvements on previous studies, 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.

Building from studies looking at patterns 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 used US Toxic Release Inventory (TRI) data and 1990 census tract-level estimates of respiratory air toxics risk to predict 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 predictors 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 toxins 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 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.

Building off these important 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 make four methodological improvements. 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 used 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.

2.2. Materials and Methods

2.2.1 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 (U.S. Customs and Border Protection 2014), transporting manufactured products from Ciudad Juárez *maquiladoras*.

El Paso is also home to three substantial non-road mobile sources of pollution: the El Paso International Airport, Fort Bliss, which includes the U.S. 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).

2.2.2 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. The percent Hispanic in our sample was 82.2% versus 82.6% for all EPISD fourth and fifth graders and 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.

2.2.3 Variables

2.2.3.1 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 five 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.

Table 2.1: Descriptive statistics for GPA, respiratory and diesel PM NATA air toxics risk estimates by source, and control variables

Variable	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	142.5	20000	2612.8	2050.1	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 is male	1835	0	1	0.5	0.5	3.2
Child's age	1862	8	13	10.4	0.8	1.7
Free/reduced priced meals	1656	0	1	0.6	0.5	12.6
Teenage motherhood	1633	0	1	.09	.282	14
Mother's education	1692	1	21	13.06	3.9	10.7
Mother is Hispanic	1672	0	1	0.8	0.4	11.8

Mother is non-Hispanic black	1700	0	1	0.02	0.2	10.3
Mother's English proficiency	1655	0	3	2.2	1.0	12.7

2.2.3.2 Air toxics variables

We used the USEPA's 2005 National-Scale 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). The 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 respiratory and diesel PM risks, the EPA first uses the data from the National Emissions Inventory (NEI) and inputs it into the a Guassian 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 calculation routines, the HAPEM5 model uses human activity patterns, census population data, ambient air quality levels, meteorological information, and indoor/outdoor concentration relationships to estimate an expected range of inhalation exposure concentrations for groups of individuals. 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 2011). 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 2011)

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 include emissions from factories, refineries, and power plants; (5) *non-road mobile respiratory risk* which include emissions from mobile sources not found on roads and highways e.g., airplanes, trains, and construction vehicles; and (5) *non-point* (formerly called "area") *respiratory risk* which include 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). 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 2.1 and standardized versions of all NATA variables are used in the models.

2.2.3.3 Control variables

We adjust for eight individual-level control variables that were selected based on a review of the children's academic performance literature. Poverty 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. Guidelines for constructing this variable were obtained from the 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. We used this variable instead of poverty because it is a less conservative measure of socioeconomic disadvantage then is poverty. Free or reduced price meals is 185 % percent of the poverty line. 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 simulating 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 school tracking, parenting skills, and family structure (Duncan and Magnuson 2005). 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.

2.2.3.4 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.

2.2.4 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 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, and provide a general method for the analyses of clustered continuous, ordinal, dichotomous, polychotomous and event-count response variables, while relaxing 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, 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.

2.3. Results

2.3.1 Correlations

Correlations are presented in Table 2.2. All eight NATA variables were negatively and significantly ($p<.01$) correlated with lower GPAs, although the respiratory point risk estimate had the weakest correlation of the eight. In terms of the relationship between GPA and the control variables, qualifying for free and reduced price meals and having a Hispanic mother were negatively ($p<.01$) correlated with GPA. Males had lower GPAs than females ($p<.05$). The mother's years of education and the child's age were positively ($p<.01$) correlated with GPA.

Table 2.2: Correlation matrix

Variables	1	2	3	4	5	6	7	8	9	10
1. GPA										
2. Total respiratory[a]	-.229**									
3. Total diesel PM[b]	-.220**	.985**								
4. Child is male	-.065*	-.004	-.004							
5. Child's age	-.081**	.037	.033	.019						
6. Free/reduced price meals	-.278**	.304**	.296**	.031	.082**					
7. Teenage motherhood	-.083*	.072*	.067	.027	.051*	.115**				
8. Mother's education	.314**	-.295**	-.288**	.012	-.101**	-.410**	.-083**			
9. Mother is Hispanic	-.135**	.212**	.202**	-.021	.025	.268**	.062*	-.221**		
10. Mother is non-Hispanic black	-.072	.007	.009	.028	.028	-.014	.024	.011	-.267*	
11. Mother's English proficiency	.039	.062	.052	-.015	.041	.089**	.016	-.003	.272**	-.116

Note: *p<.05, **p<.01

[a] The correlations between all variables and point, on-road mobile, non-road mobile, and non-point respiratory risk estimates agree in direction and significance with the total respiratory risk correlations and are therefore not presented.

[b] The correlations between all variables and on-road and non-road diesel risk estimates agree in direction and significance with the total diesel risk correlations and are therefore not presented.

2.3.1 GEE Results

For respiratory risk (see Table 2.3), all sources of respiratory risk except for point were statistically significant and negatively associated with GPA. Non-road respiratory risk had the strongest effect on GPA (B=-0.036, *p*=.001) of the sources tested; for every one standard deviation increase in non-road respiratory risk, the average student's GPA decreased by 0.036 points.

Table 2.3: Results of the Respiratory Risk GEE Models Predicting Child's GPA

	Model 1		Model 2		Model 3		Model 4		Model 5	
Air toxic respiratory risk variable included in the model:	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

[a] Variable was standardized before being entered into the model

In terms of the findings for the diesel PM risk variables (see Table 2.4), all three variables were statistically significant and negatively associated with GPA. Non-road diesel PM had the strongest effect on GPA (B= -0.035, *p*<.001). This corresponds to a .035 point decrease in GPA for every one standard deviation increase in non-road diesel PM risk. In terms of the control variables (see Tables 3-4), being male, qualifying for free and reduced price meals and having a mother with lower levels of education were statistically significantly associated with a lower GPA. The other five control variables were not significant.

Table 2.4: 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

[a] Variable was standardized before being entered into the model

2.3.3 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. Longitudinal data would have supported stronger inferences than the cross-sectional approach implemented here, and future studies should employ longitudinal designs. 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 EPISD demographics as a whole, the 30% response rate may be improved upon through the use of multimode data collection designs.

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 stable between 2005 and 2012. 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 NATA does not account for how pollutants interact with each other (Chakraborty 2009) and cannot be used to identify hot spots where the ambient concentration, exposure, or risk might be significantly higher within a geographic unit (Chakraborty 2009). Using census block groups as opposed to census tracts helps to partially address this. 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.

2.4. 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 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. The coefficient for the point source respiratory risk was not significant in the multivariate model, although it was significant in the bi-variate correlations. The fact that all but one air toxics variables remained significant even when controlling for parental, socio-demographic and school-level effects indicates that residential exposure to air pollution has an independent effect on children's academic performance that cannot be dismissed with explanations of poverty, 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.

There are two pathways through which the air toxic exposures examined here likely influence children's academic performance. 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).

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 the robustness of the 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 is 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 particulate 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. 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.

2.5. 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 toxins by source and our analysis illustrates the utility of doing so. These findings clarify the pollutant sources that have the greatest impact on children's academic performance, which can help shape 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. Our documentation of the impact of non-road mobile air toxics on reduced academic performance in El Paso is novel.

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 poverty (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' for many El Paso youth (Institute of Medicine Committee on Environmental Justice, 1999). 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 robust 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 look more like 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.

CHAPTER 3

CHILDHOOD HEALTH STATUS, AIR TOXICS, AND ACADEMIC ACHIEVEMENT

3.1. Introduction

The impact of children's health status on academic achievement has been well studied but the findings have varied widely across health conditions (Case et al. 2002; Forrest et al. 2012; Eide et al. 2010). Researchers have focused on health outcomes such as obesity, asthma, depression, and Attention Deficit Hyperactivity Disorder (ADHD), which have been negatively correlated with absenteeism (Pan et al. 2009; Silverstein et al. 2001) and academic achievement outcomes (Kramer et al. 1995; Forrest et al. 2012; Fowler et al. 1985; Eide et al. 2010; Currie and Stabile, 2005). Others have found no link between children's health and academic achievement, especially for conditions such as asthma, where medications have improved in recent decades (Silverstein et al. 2001). Studies examining the relationship between children's general health status and academic achievement have found that poorer health is associated with worse school performance outcomes (Le et al. 2013; Spernak et al. 2006). Overall, when children are unhealthy, they may have more difficulty learning than their healthy counterparts and have lower GPA's and standardized test scores (Basch, 2011).

A critical limitation of these studies has been that they have not included the impacts of environmental toxins on children's academic performance, which have been shown to be significant influences (Pastor et al. 2004; Pastor et al. 2006; Mohai et al. 2011; Scharber et al. 2013; Lucier et al. 2011; Currie et al. 2009). Researchers have found that exposure to air pollutants can put children at risk for respiratory illnesses, which causes them to miss school, which can negatively impact their learning, grades, and standardized test scores (Pastor et al. 2004; 2006). When children are continuously exposed to air toxics, their cognitive and neurological development may also be delayed or impaired and they may have lower grades and standardized test scores because of it (Guxens and Sunyer, 2012). The strength of the association between air toxics and reduced school performance suggests that the impact of environmental toxins may at least partially account for the relationship between poor health and reduced school performance observed in other studies. Exposure to air toxics may also intensify the association between poor health and school performance. But because the school health literature and the environmental justice literatures have remained largely separate, these hypotheses have yet to be investigated.

To address this gap, we examine the association between children's health status, air toxics risk estimates at children's home sites and children's grade point averages among a representative, population-based sample of 4th and 5th graders in El Paso, Texas. The primary research questions and hypotheses are: (1) Does children's general health status, particularly poor health, negatively impact children's school performance outcomes, independent of relevant covariates? Based on prior studies, we hypothesize that children who have lower general health status scores will have lower GPAs than their healthier peers (2) Does residential exposure to environmental toxins still significantly impact GPA, when accounting for children's health status? We hypothesize that air toxins will be a significant predictor of GPA, but that they will not completely explain away the association between health status and air toxins. This would suggest that there is an independent effect of exposure to air pollution on children's school performance that is not explained by poor health. If only health status is significant and air toxics are not, it would suggest that poor health may account for the impacts of exposure to air pollution on GPA reported in Chapter 2, meaning exposure to pollution may be responsible for poor health that then negatively impacts academic achievement outcomes. If only air toxics are significant and poor health is not, it would suggest that exposure to air pollution is responsible for decreased academic achievement and that poor health is not. Finally, we ask 3) Does exposure to air toxics modify the association between children's health status and GPA? We hypothesize that negative association between health status and GPA will be stronger for children who have higher levels of residential exposures to air toxics.

While some studies of health and school performance look at specific health conditions, often asthma or obesity, others examine general health status as a holistic measure of children's health. Health status is usually measured using the general health status variable (response options ranging from "poor" to "excellent") (Spernak et al. 2006; Le et al. 2013) or by creating a composite variable that is a sum of the number of chronic health conditions affecting a child (Eide et al. 2010; Forrest et al. 2012). Studies using both types of measures have demonstrated similar results, which is that worse children's health status is linked to lower levels of academic achievement.

Most recently, Le et al. (2013) examined the impact of poor childhood health on educational progress using three waves of longitudinal data over a 10 year period. The children's health status measure was dichotomized into good health ("excellent" and "very good") and poor health ("good", "fair" or "poor"). Using linear regression, Le et al. (2013) found that for students who were older at baseline (11-14 compared to 5-7 year olds), poor health was associated with fewer years of completed schooling ten years later, at the final wave of the survey and these findings were more pronounced for those who reported poor health at all three waves. Using data from the National Head Start-Public School Early Transition study (NDTS), which also included students who had not attended Head Start, Spernak et al. (2006) found, using hierarchical linear regression and controlling for family income, maternal education and minority status, that by the third grade, better health status was significantly associated with higher academic achievement outcomes.

When specific physical illnesses are studied, the findings are less robust. While children with asthma miss school more frequently, asthma is only weakly associated with reduced school performance (Taras and Potts-Datema, 2005). There is also limited evidence that obesity results in reduced school performance (Kaestner and Grossman, 2009), even though it is often associated with diabetes, hypertension, bullying, depression and low self-esteem (Pan et al. 2012). The findings for general health status more consistently show an association between poor health and reduced school performance, which is why we focus on it here in our examination of air toxics, children's health and GPA.

Exposure to toxic chemicals and their effect on school performance has been an area of interest for environmental justice (EJ) researchers. Children are more physiologically vulnerable to the effects of toxic air pollution than adults are (Pastor et al. 2004; Currie et al. 2009) and toxins can harm their developing respiratory and neurological systems. A handful of studies have examined the relationship between air pollution and children's academic performance outcomes at the level of the school and have found a negative association between exposure to air pollution and student school performance. One of the first studies to do so used US Toxic Release Inventory (TRI) data and 1990 census tract-level estimates of respiratory air toxics risk to predict aggregated standardized test scores for schools in the Los Angeles Unified School District. Pastor et al. (2004) found that the risks from air pollution exposure at school were negatively and statistically significant predictors of standardized test scores adjusting for school demographics. In a follow up study that included all public schools in California, Pastor et al. (2006) found that the general pattern observed in the LAUSD held for the rest of the state. Outside of California, similar studies have been conducted in Baton Rouge, Louisiana schools, with similar significant findings (Lucier et al. 2011; Scharber et al. 2013).

In this paper we estimate how children's general health status and exposure to toxic air pollution impacts grade point average (GPA). Building off of previous studies, we make several improvements. First, prior studies have examined the impacts of health status and exposure to toxic pollution on academic performance outcomes separately, but to our knowledge, this is the only study to examine both together. Second, while the health/school performance studies are often conducted at the individual level, the air toxics/school performance studies are usually done at the level of the school. Our student-level data, collected through a mail survey, enables us to study individual children, rather than schools. Given the ecological fallacy, one cannot assume that the relationship found at the level of the school exists at the level of the individual. Third, we used Generalized Estimating Equations (GEE) instead of OLS regression, which allow us to adjust for clustering by school and thus isolate the individual-level effects of general health status and the residential air toxics risk indicators. 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. Since GEE's account for non-normality in distribution, we are able to improve on previous studies by treating the health status indicator as a continuous, rather than dichotomous, variable. This enables a more nuanced look at children's health status than a dichotomous variable would allow.

3.2. Materials and Methods

3.2.1 Study context

The study took place in El Paso, Texas. El Paso is located on the US- Mexico border and had an estimated population of 640,066 in 2011 (US Bureau of the Census). The population is

81% Hispanic, compared to 17% of US population and 38% of the Texas population are Hispanic. About 14% of El Paso residents were non-Hispanic white while 4% were non-Hispanic black. El Paso has a high rate of poverty (24% in 2011) that is significantly greater than the national rate (16%). El Paso is also home to a bilingual populace. In 2011, 26% of residents spoke English only, while 72% spoke Spanish; among Spanish speakers, 27% were not English proficient. Among El Paso residents, 26% were foreign-born, and 15% were not US citizens.

Air quality is a major concern in El Paso. El Paso is rated among the highest of Texas cities for carbon monoxide levels (Currie et al. 2009) and 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. El Paso is also home to many large-scale polluting facilities such as Western Refining, Phelps Dodge Copper Products, and those associated with Fort Bliss and its U.S. Army Air Defense Artillery Center, 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 U.S. Army Air Defense Artillery Center.

3.2.2 Data collection

Socio-demographic, general health status, and academic performance data were collected through a cross-sectional mail survey. The survey 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 10^{th} largest district in Texas and the 61^{st}

largest district in the United States. In 2012, there were over 64,000 students enrolled in the district and there were over 94 campuses throughout El Paso County.

We used the Tailored Design Method to obtain the highest response rate possible (Dillman et al. 2009) for the survey. We first 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 next week we sent out a bilingual reminder postcard to non-respondents, and the third week, we resent the survey package to all households that had not responded. A total of 6,295 surveys were delivered to the caretakers; 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); our sample was generally representative of the demographics of EPISD fourth and fifth graders. The percent Hispanic in our sample was 82.2% versus 82.6% for all EPISD fourth and fifth graders and the percent of students qualifying for free or reduced price meals was 60.4% 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. The majority of the primary caretakers were mothers (83%); 10% were fathers, 4% were grandparents, 1% were step-parents, and another 1% were aunts/uncles. Secondary caretakers were primarily fathers (57%), while 24% were mothers, 6% grandparents, 10% step-parents, and 1% aunts/uncles.

Six children were excluded from this analysis because they fell 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 in which the parent completed the survey. Because our statistical model 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. This means that data from 1,895 children are analyzed in this paper.

3.2.3 Variables

3.2.3.1 School Performance Outcome

We use Grade Point Average (GPA) as the academic performance measure in this study. The caretaker was asked "What grades has your child received in the following subject areas (an A=90-100; B=80-89; C=70-74; F=0-69)? The subject areas were reading, language arts, math, social studies, and science. The list of subjects and grades included in the survey was taken from an official EPISD report card. We then recoded this variable so that F=0, D=1, C=2, B=3, A=4. Scores were then summed and divided by five to create the continuous GPA dependent variable. Descriptive statistics are presented in Table 3.1. On average, children did well in school and had a mean GPA of 3.3 (out of a 4.0). The grade distribution in our sample follows the national pattern for grades received in elementary school. According to U.S. Department of Education data (Digest of Education Statistics, 2009), 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.

Table 3.1: Descriptive Statistics for all analysis variables

	N	Minimum	Maximum	Mean	SD	% Missing
GPA	1690	0.2	4	3.3	0.7	10.8
Total respiratory risk	1895	0.6	6.88	1.94	0.86	0
Total diesel pm	1895	0.12	7.93	1.3165	1.06	0
Child is male	1835	0	1	0.5	0.5	3.2
Child's age	1862	8	13	10.4	0.8	1.7
Fee/reduced priced meals	1656	0	1	0.6	0.5	13.7
Teenage motherhood	1643	0	1	0.086	0.28	14
Mother's education	1692	1	21	13.1	3.9	10.7
Mother is Hispanic	1672	0	1	0.8	0.4	11.8
Mother is non-Hispanic black	1700	0	1	0	0.2	10.3

Mother speaks English	1655	0	3	2.2	1	12.7
Child's general health status	1878	2	6	5.1	0.9	0.9

3.2.3.2 Health Status Variable

General health status is measured using a survey question from the International Study of Asthma and Allergies in Childhood survey that asked "How would you describe the overall health of the child? (6=excellent, 5= very good, 4= good, 3= fair, 2= poor, 1=very poor). Child's general health status has also been used in previous studies of school performance outcomes (Le et al. 2013, Spernak et al. 2006). We used child's general health status, rather than a more specific predictor of health (e.g., asthma), because general health status encompasses a wide range of health conditions. Previous studies have found associations between health status and years of schooling (Le et al. 2013) and test scores (Spernak et al. 2006) and many children's health issues are co-morbid with one another, making it hard to disentangle effects of specific chronic conditions on academic achievement. Research has demonstrated that self-reported health most closely reflects physical symptoms, as compared to mental health (Bailis et al. 2003). General health status is also a well-established variable that has been widely used in gathering information on people's health and is reliable because both medical professionals and lay people share a general understanding of health (Jylha, 2009).

In Texas, children's general health status is similar to US national averages; 82.0% of caretakers in Texas said their child had excellent or very good health versus 84.2% nationwide, while 14.2% said their child had good health, compared to 12.7% nationwide (Data Resource Center for Child and Adolescent Health, 2012). In our sample, 72.9% percent of caretakers said their children had excellent or very good health while 20.8% of caretakers said their children had good health. While Le et al. (2013) and Spernak et al. (2006) dichotomized general health status, we were able to treat child's general health status as a continuous variable because one can include non-normally distributed variables in a Generalized Estimating Equation (GEE) without violating assumptions.

3.2.3.3 Air Toxics Variables

Air toxics data were obtained from the US Environmental Protection Agency (EPA) 2005 National Scale Air Toxics Assessment (NATA) census block-level database. This dataset includes all hazardous air pollutants regulated by the Clean Air Act (except criteria pollutants) that are known or suspected to cause cancer or neurological, respiratory, immunological or reproductive diseases (Environmental Protection Agency 2013b). Currently, NATA is the best secondary data source for spatially explicit characterization of air toxics risk exposure in US metropolitan areas (Roberts et al. 2013; Linder et al. 2008; McCarthy et al. 2009; Su et al. 2009; Marshall et al. 2014). We used the results from the 2005 NATA because it was the most recent available dataset. The USEPA works with states and industries to gather data about air toxics emissions and then compiles them into the NATA. The methodology used by the USEPA assumes that the risks of differing pollutants are additive and can be totaled to estimate an aggregate risk score for each geographic unit.

To calculate the estimates for respiratory and diesel PM risks, the USEPA 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, the 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 calculation routines, the HAPEM5 model uses human activity patterns, census population data, ambient air quality levels, meteorological information, and indoor/outdoor concentration relationships to estimate an expected range of inhalation exposure concentrations for groups of individuals. 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 both the respiratory and diesel PM risk are indicated 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 USEPA uses the RfC as part of a calculation known as 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 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 estimation 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 negative effects will occur, a HI greater than 1.0 indicates the potential for adverse effects (Environmental Protection Agency 2011). Unfortunately, the USEPA 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, 2011).

For the air pollution variables, we use *total respiratory risk,* which is the summation of all respiratory risk variables in the NATA which include background and secondary risk estimates. We also *total diesel particulate matter (PM)* which captures only non-cancer (i.e., respiratory and cardiovascular) health effects. We assigned these 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. The block level estimates that we use in this study were received directly from the USEPA and are at a finer spatial resolution than the publically available census tract estimates that are used to assign risk values to children's home addresses in other studies (Roberts et al. 2013). The USEPA weights the block level values based on population in order to construct the publically available census tract-level values, published on the USEPA's website. The NATA variables in our dataset were standardized for inclusion in the statistical models and descriptive statistics for these variables are presented in Table 1.

3.2.3.4 Control variables

In this study, we adjust for ten individual-level variables associated with children's academic performance. Previous research indicates that poverty is linked to decreased academic performance (Reardon and Galindo, 2009). It is represented by (1) qualifying for free or reduced price meals at school. Guidelines for constructing this variable were obtained from The Food and Nutrition Service (FNS) of U.S. Department of Agriculture (USDA). We used the two following survey questions in our calculations: 1) How many people are living or staying at this (reported) address? 2) What is your yearly total household income for 2011 before taxes (1=Less than 1,999 – 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. We used this variable instead of poverty because it is a less conservative measure of socioeconomic disadvantage then is poverty. Free or reduced price meals is 185 % percent of the poverty line. A total of 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) teenage motherhood because children born to teenage mothers tend to fare worse in school as it is more challenging for these mothers to provide educationally simulating 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.

Having a (4) black/African American and/or (5) Hispanic mother have been associated with lower levels of academic performance among children. The academic achievement gap between students of color and white students has been well studied and documented (Reardon and Galindo, 2009; Kao and Thompson, 2003; Duncan and Magnuson, 2005; Bali and Alvarez, 2003). It likely stems from multiple social factors such as disadvantageous educational tracking, parenting skills, and family structure (Magnuson, 2007). To determine whether the mother was Hispanic or non-Hispanic black, we drew from two questions that asked, "Are you of Hispanic, Latino, or Spanish origin?" and "What is your race?" Each question transformed into its own variable with a 0=no and 1=yes response (i.e. Hispanic: 0=no; 1=yes; non-Hispanic black: 0-no;

1=yes). In our sample, 80% of mothers were Hispanic while another 2% were non-Hispanic black.

We adjust for (6) mother's English proficiency because mothers who are not proficient in English may be unable to help with homework and also may be less familiar with the US public school system and its expectations (Reardon and Galindo, 2009). Mother's English proficiency was measured using the survey 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 and the mothers had an average score of 2.17 for English proficiency. We also adjust for (7) children's current age and the (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 children in the survey were 8, while the oldest were 13. Both males and females were equally represented in the sample (the sample was 50% male and 50% female).

3.2.3.5 Schools

We control for clustering at the level of the school because the school context is a known influence on children's academic performance (Mohai et al. 2011). The Generalized Estimating Equations (GEEs) we estimate statistically account for school-level effects as a nuisance, enabling us to isolate the effects of the individual-level residential air toxics risk and general health status 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 attending one school was 8, while the maximum was 61.

3.2.4 Analysis 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 can occur when values are not missing completely at random (Penn, 2007). We imputed missing values for multiple datasets (n=20) to increase power using a regression-based approach, and specified 200 between-imputation iterations to ensure independence among the datasets (Enders, 2010). Using 20 as opposed to 3–5 datasets improves the validity of multi-parameter significance tests (Enders, 2010). MI techniques appropriately adjust the standard errors for missing data (Enders, 2010).We included all relevant variables in the MI procedure. The percent missing for the variables ranged from 1.7% (age of the child) to a high of 13.7% (teenage motherhood). We analyzed the multiply imputed data using correlations and Generalized Estimating Equation (GEE) analyses with robust (i.e., Huber/White, sandwich, empirical) covariance estimates. GEEs extend the generalized linear model (Nelder and Wedderburn, 1972) to accommodate data that is correlated and provide a general method for the analyses of clustered continuous, ordinal, dichotomous, polychotomous and event-count response variables. GEE's also relax several assumptions of traditional regression models. For this analysis, GEEs enable us to examine the associations between general health status, air toxics risk and GPA (all non-normally distributed variables), while accounting for school-level effects.

For this analysis, 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 generate 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). 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). 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 address our first research question, we ran a GEE model that analyzed the effect of child's general health status on GPA, while controlling for the sex of the child, age of the child, poverty (free or reduced price meals), mother's age at the birth of child, mother's education, whether the mother is Hispanic or non-Hispanic black and how well the mother speaks English. For the second research question, we conducted a second GEE analysis and ran two separate models. Each model analyzed the effects of child's health status and exposure to one of the air toxics variables on academic performance, while adjusting for the same covariates as in the first model. In the models, we included a different air pollution variable (total respiratory risk and total diesel PM risk) to examine the effects of exposure to air pollutants from a range of sources posing different types of health risks. We could not include multiple air pollution variables together in any single model due to concerns about multicollinearity. To address the third research question, we interacted each of the NATA variables with health status in another two

GEE models (one for each air toxics variable). All interactions were performed in SPSS using the interaction specification in GEEs.

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 three models, so we used this specification. Due to the exploratory (as opposed to confirmatory) nature of the analysis, we did not correct for multiple comparisons (Bender and Lange, 2001) and we employed two-tailed tests of significance.

Table 3.2: Correlations Matrix

Variables	1	2	3	4	5	6	7	8	9	10	11
1. GPA											
2. Child's health status	0.228**										
3. Total respiratory risk	0.229**	-0.184**									
4. Total diesel risk	0.220**	-0.178**	0.985**								
5. Sex of the child	-0.060**	-0.061**	-0.005	-0.005							
6. Child is male	-0.082**	-0.035**	0.038**	0.032**	0.019**						
7. Free/reduced price meals	-0.257**	-0.248**	0.296**	0.288**	0.032**	0.081**					
8. Teenage motherhood	0.081**	0.017**	-0.064**	-0.057**	-0.026	-0.054**	-0.113**				
9. Mother's education	0.334**	0.282**	-0.324**	-0.315**	0.014	-0.105**	-0.398**	0.079**			
10. Mother is Hispanic	-0.150**	-0.179**	0.217**	0.207**	-0.019**	0.031**	0.267**	-0.055**	-0.232**		
11. Mother is non-Hispanic black	-0.078**	0.002	0.021**	0.023**	0.029**	0.034**	-0.012*	-0.027**	-0.012*	-0.225**	
12. Mother speaks English	0.022**	-0.050**	0.077**	0.066**	-0.007	0.041**	0.111**	0.021	-0.015**	0.249**	-0.061**

Note: *p<.05, **p<.01

3.3. Results

3.3.1 Correlations

Correlations are presented in Table 3.2. The NATA variables were negatively and significantly ($p<.01$) correlated with lower GPAs and lower child's health status. In terms of the relationship between health status and the control variables, qualifying for free and reduced price meals ($p<.01$), teenage motherhood, and having a Hispanic mother ($p<.01$) were negatively correlated with child's health status. Males had lower GPAs than female students ($p<.01$). The child's age ($p<.01$), mother's years of education, and mother's English proficiency were positively correlated ($p<.01$) with better health status.

In terms of the relationship between GPA and the control variables, qualifying for free and reduced price meals ($p<.01$), teenage motherhood ($p<.01$) and having a Hispanic mother or a non-Hispanic black mother ($p<.01$) were negatively ($p<.01$) correlated with GPA. Males had lower GPAs than females ($p<.01$). The mother's years of education ($p<.01$), the child's age ($p<.01$), and mother's English proficiency were positively correlated with GPA.

3.3.2 Results for the Generalized Estimating Equations (GEE)

In terms of the results for our first research question, child's health status was positively and significantly associated with GPA, adjusting for relevant covariates. In terms of the control variables (see Table 3), being male, qualifying for free or reduced price meals, and having a mother with lower levels of education were statistically significantly associated with a lower GPA. Mother's English proficiency was positively and significantly associated with child's GPA. Having a non-Hispanic mother was associated with greater GPA and the parameter was nearly significant ($p=.071$).

Table 3.3: Results of the GEE Models Predicting Child's GPA

	Model 1		Model		Model 3	
	Health Status		Total Respiratory		Total Diesel	
	β	Sig.	B	Sig	β	Sig
Child is male	-0.027	0.028	-0.028	0.025	-0.027	0.026
Child's age	-0.011	0.112	-0.012	0.108	-0.012	0.107
Free/reduced price meals	-0.057	0.029	-0.050	0.055	-0.051	0.052
Teenage motherhood	0.037	0.175	0.036	0.185	0.037	0.179
Mother's education	0.061	0.000	0.059	0.000	0.059	0.000
Mother is Hispanic[a]	-0.052	0.071	-0.047	0.104	-0.048	0.98
Mother is non-Hispanic black[a]	-0.101	0.182	-0.099	0.195	-0.099	0.194
Mother speaks English	0.017	0.030	0.018	0.027	0.018	0.028
Child's general health status	0.035	0.000	0.034	0.000	0.034	0.000
Air toxics risk	n/a	n/a	-0.023	0.004	-0.021	0.009

In the next step, air toxic variables were added to the models (see Table 3.3). Across both models, child's health status remained positively and statistically significant, meaning that for every one unit increase in health status, the students GPA increased by 0.034 points. In terms of the findings for the NATA variables, both variables (total respiratory risk and total diesel PM risk) were significantly and negatively associated with GPA, controlling for the other variables in the model. In terms of control variables, the findings were similar in terms of direction and significance as they were in model 1.

In a third step, we added interactions between the air toxics variable and health status, but none of the three terms approached significance (p>0.10) so the tables are not reported.

3.3.3 Sensitivity analysis

To test whether the coding of the health status variable (continuous vs. dichotomized) would significantly impact results, we repeated our analysis using a dichotomized indicator (1=excellent/very good health vs. 0=good/fair/poor/very poor health) as a sensitivity analysis. When we instead use dichotomized health status, the direction and significance of the health status and air toxics betas did not change. In model 1, the beta for health status was .058, compared to .035, when using the continuous indicator. In model 2, the betas for health status and respiratory risk were .056 and -.024, respectively, compared to .034 and -.023 when using the continuous indicator. Lastly, in model 3, the betas for health status and diesel PM risk were .056 and -.021, respectively, compared to .034 and -.021 when using the continuous indicator.

As a second sensitivity analysis, we ran subgroup models for boys and girls to examine whether the findings might be different for boys or girls, which was the case in a previous study (Eide et al. 2010). Here, health status and the air toxics risk variables remained statistically significant for both boys and girls.

3.4. Discussion

The findings from this study serve to illustrate the importance of both health status and exposure to air toxics on children's academic achievement. When studied separately, both pollution (Pastor et al. 2004; Pastor et al. 2006; Scharber et al. 2013; Lucier et al. 2011) and health status (Le et al, 2013; Spernak et al. 2006) are known to be important predictors of academic achievement in childhood. There are multiple ways in which children's health status can impact GPA. Poor health status in childhood can influence cognition and ability to retain information learned in school and can increase absenteeism, all of which are negatively associated with GPA (Basch, 2011). These pathways can then influence the likelihood that a student will drop out of school or decide not to pursue post-secondary education. This illustrates why children's health status is an important predictor of academic achievement in childhood (Basch, 2011) and highlights how health status at a young age may also influence the trajectory of one's life by impacting health, socioeconomic status, and employment in adulthood (Case et al. 2005).

While the multiple factors that influence academic achievement are impossible to disentangle, the results from our study suggests that, in addition to health status, residential air toxics exposure also affects GPA. Exposure to air toxics poses multiple types of dangers, including those to cognitive and respiratory health systems. In our study, we found that the impact of residential air toxics on GPA was significant even when accounting for health status. Related to Research Question 3, we hypothesized that poor health might intensify the association between residential exposure to toxic pollutants and academic achievement but did not find this. The effect of air toxics on GPA was not modified by poor health. The fact that both health status and air pollution are statistically significant suggests that there is an independent effect of air toxics on academic achievement that cannot be explained by poor health alone. This suggests the hypothesis that toxins are linked to developmental delays, which then manifest in lower GPAs. It is plausible that the cognitive effects of air toxics, which would impact children's ability to learn and therefore their GPAs, may be so insidious that they are difficult for parents to recognize, and thus would not be included in a parent report assessment of their child's health. Future research is needed to test this. It may also be that exposure to toxins is also responsible for increased absenteeism, thus causing a decrease in GPA, but we did not have data to test this. A next step could be to employ a path model to analyze the different mechanisms through which exposure to air pollution might impact GPA.

Previous studies have primarily concentrated on the respiratory risks associated with polluting facilities (Pastor et al. 2004; 2006), while studies on the health risks related to diesel PM are only beginning to appear in the literature (Roberts et al. 2013; Habre et al. 2014). While diesel PM is associated with both acute and chronic health effects (Environmental Protection Agency, 2014), our findings show that diesel PM may also negatively impact children's GPA.

Previous studies have suggested that schools should not be placed near point sources of pollution and other hazardous sites and vice versa (Pastor et al. 2006; Mohai et al. 2011); we extend this recommendation to include airports and railroads, because they are the primary sources of diesel PM in El Paso.

It must be noted that others (e.g., Bzostek et al. 2007) have identified issues with the use of the general health status variable especially when surveys are collected in Spanish and English. Self-rated health is often measured, as we did here, using a scale of one to six with the labels "excellent", "very good", "good", "fair", "poor" and "very poor" in English and "*excelente*", "*muy buena*", "*buena*", "*regular*", "*mala*" and "*muy mala*" in Spanish. While this item is widely used in health research, some have argued that the Spanish translation does not directly align with the English translation. In Spanish, "*regular*", can mean, "fine" or "okay" health, while in English, "fair", more clearly signifies sub-optimal health (Bzostek et al. 2007). Because of this, Spanish speaking survey respondents may be more likely to rate their health lower than a respondent with an English-version survey. This is the case in our data as those who responded to the survey in Spanish rated their children's general health status 4.74 out of 6, while those who responded in English rated their children's general health status 5.24 on average. We did control for the mother's English proficiency in the models, which may have addressed this limitation to a degree.

3.5. Conclusion

Previous studies have examined academic achievement and exposure to air toxins and health status separately; none have looked at the relationship between health and air toxins combined. 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), in addition to the impact of poor health on GPA in childhood. In sum, the finding that there is a robust association between worse children's health status, higher residential exposure to air toxics and lower GPAs at the individual level is both novel and disturbing. We corroborate previous studies that have linked health status to academic achievement and 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 (adjusting for general health status). While El Paso is socio-demographically unique, it serves as a model for how other US cities will start to look in the coming decades as the Hispanic population continues to grow nationwide. The results of this study also contribute to a broader understanding of the relationship between children's general health status and academic achievement. These findings provide another piece of evidence that should inform advocacy for pollution reduction in the US and beyond.

CHAPTER 4

SUMMARY AND CONCLUSIONS

4.1 Summary

This thesis has examined the relationship between exposure to air toxics and children's academic achievement (Chapter 2), including a consideration of the role of health status in children's academic achievement (Chapter 3). A handful of studies have examined the impacts of exposure to air toxics on children's academic achievement (Pastor et al. 2004; Pastor et al. 2006; Scharber et al. 2013; Lucier et al. 2011), but these have all be conducted at the level of the school. Problems associated with this were discussed in Chapter 2. Additionally, others have investigated the effect of health status on children's school performance (Le et al. 2013; Spernak et al. 2006), but none have included the role of air toxics. To our knowledge, this is the first study to examine individual-level effects (in Chapters 2 and 3) and to consider both health and air toxics together (in Chapter 3).

In Chapter 2, we examined if exposure to air toxics significantly impacted children's GPA, independent of individual-level factors. Based on prior studies, we hypothesized that children who have higher levels of residential air pollution would have lower GPAs. Using generalized estimating equations (GEEs), we found that all but one of our 8 NATA air toxics variables were statistically significantly associated with decreased school performance in children. Additionally, because we were able to disaggregate the NATA air toxics risk estimates by health effect and source, we uncovered that non-road mobile respiratory sources had the largest effect on GPA (B=-.036), as compared to point sources (B=-.010) (e.g. large factories and refineries), which was our one air pollution variable that did not reach significance. The finding means that a one standard deviation in non-road mobile sources of pollution was tied to a .036 point decrease in GPA.

In Chapter 3, we examined three research questions. First, we tested if children's general health status, particularly poor health, negatively impacted children's school performance outcomes, independent of relevant covariates. Based on prior studies, we hypothesized that children who had lower general health status scores would have lower GPAs than their healthier peers. We found that EPISD children with poorer health had significantly lower GPAs than their healthier counterparts, which corroborates previous research (Le et al. 2013; Spernak et al. 2006). Second, we explored whether children's general health status still significantly impacted GPA, when accounting for residential exposure to environmental toxins. We hypothesized that air toxins would be a significant predictor of GPA, but that they would not completely explain away the association between health status and air toxins. In our GEE models, both health status and the NATA air toxics variables remained statistically significant, meaning that the impact of air pollution on GPA was significant even when children's health status was controlled for. Third, we examined whether exposure to air toxics modified the association between children's health status and GPA. We hypothesized that negative association between health status and GPA would be stronger for students who had higher levels residential exposures to air toxins. We did not find that exposure to toxic pollutants intensified the relationship between poor health and academic achievement. This meant that the effect of poor health on lower GPA was not affected by air toxics, and vice versa.

4.2 Policy Implications

Two of the most important findings stemming from this research are: (1) that non-road mobile sources, including diesel, had the larger effects on GPA than did toxins from point and on-road mobile sources; and (2) that health status and air toxics were both statistically significant when included in the same model, which suggests that there is an independent effect of pollution on academic achievement that cannot be explained by poor health alone. El Paso is home to many large scale pollution sources (e.g. an international airport and rail road system) that are common throughout many large US cities. Our finding that non-road mobile sources of pollution had the largest effect on GPA in Chapter 2 suggests that children's exposure to pollution from airplanes, construction vehicles, and trains is more detrimental than has previously been recognized and this finding may be 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 should increasingly be recognized nationwide.

In line with other studies, the findings from Chapter 2 emphasize the need for policy to monitor and regulate toxics emissions, including those from non-road mobile sectors, like airports and rail yards. In our Chapter 2 models, non-road sources of diesel had the second highest effect on GPA (B=0.035), just following non-road mobile respiratory risk (B=-.036). The USEPA recognizes that exposure to diesel particulate matter is harmful to human health and negatively affects both the respiratory and neurological systems. There are multiple sources from which exhaust is emitted from diesel sources, included cars, trucks and buses (on-road mobile sources), but also airplanes, trains, and construction machinery and equipment (non-road mobile sources) (Environmental Protection Agency, 2014). Previous studies have suggested that schools should not be placed near point sources of pollution and other hazardous sites and vice versa (Pastor et al. 2006; Mohai et al. 2011); we extend this recommendation to include airports and rail roads, because they are the primary sources of diesel PM in El Paso. Programs targeted towards decreasing pollution from non-road mobile sources, especially diesel sources, could then be designed to increase protection and decrease risk through education and mitigation. Currently, the USEPA only recommends that drivers turn off their engines and to avoid idling in diesel vehicles, to maintain and/or retrofit a diesel vehicle engine with a pollution control device, and when purchasing a diesel vehicle, to consider the EPAs new standards before purchasing (Environmental Protection Agency, 2014). These initiatives are not sufficient to significantly reduce the diesel PM that is emitted into the air. Our findings suggest that the EPA, among other regulatory agencies at the local, state and national level, should take stronger initiatives to decrease diesel PM in the air, and to search for cleaner alternatives that are not harmful to human health.

Our findings from Chapter 3 also provide additional pieces of evidence that should inform advocacy for pollution reduction in the US and beyond. Corroborating previous studies, we found that health status is a significant predictor of school performance, and that children with poor health tend to have worse academic achievement outcomes, when compared to their healthier counterparts. In addition, we found that exposure to air pollution remains a significant predictor for decreased school performance even after health status is controlled. The combination of poor health and exposure to air toxins puts children at greater risk for poorer school performance outcomes. This is of importance because poor health in childhood has important long term consequences regarding labor and health outcomes and socioeconomic status in adulthood.

Federal agencies such as the Centers for Disease Control and Prevention have acknowledged the link between poor health and school performance, and have found that initiatives to improve health, such as school breakfast and physical education programs, have been linked to enhanced educational outcomes in children (CDC, 2015). Additional programs should be designed to for children who are chronically ill, such as tutoring and after school programs, so that these children do not fall behind in school. Lastly, because the impacts of exposure to air toxics may be not the most pertinent concern for parents of sick children or one that they can easily control, it is important that information regarding the health risks associated with continuous exposure to air toxins, as well as strategies for community-level prevention and mitigation, be distributed to parents through school-based and local community programs. Findings from this thesis will disseminated through an Op-Ed piece for the *El Paso Times*. Additionally, a short write up that summarizes the main findings from the thesis, along with pollution reduction strategies, and the two papers (post-publication) will be distributed to the El Paso Mayor, the office of the Texas Governor, the Texas Commission and on Environmental Quality (TCEQ) and the City of El Paso Department of Public Health.

4.3 Directions for Future Research

In this thesis, we were able to disaggregate the NATA air toxics data by health effect and source, and we found that respiratory and diesel pm non-road mobile sources of air pollution had the largest effect on GPA. Research examining diesel PM risk and non-road mobile sources of air pollution is only now beginning to appear in the literature, while point sources (e.g. factories and refineries) continue to receive the most attention in the policy arena. Future studies should focus on exposure to diesel particulate matter and non-road mobile sources of air toxics as systematically as point sources in order to examine the relationships between non-road mobile sources of air pollution, diesel particulate matter and health outcomes, to be able to inform policies to regulate and limit these types of emissions. Secondly, the relationship between exposure to environmental toxins and school performance is often explained through two likely pathways. The first explanation posits that children who are continuously exposed to pollution are at increased risk for respiratory illnesses, which causes them to miss school. In turn, their absenteeism negatively impacts their school performance (Mohai et al. 2011; Currie et al. 2009). The second explanation states that the pathway in which air pollution affects academic achievement is neurological. Children with neurological brain damage may have a harder time learning and retaining the material that is taught to them in school, thus reducing their school performance outcomes (Guxyens & Sunyer 2012). Future studies should examine these explanations using a path model. For example, one could examine how air toxics are associated with poor health, which is then associated with lower GPA to test the first explanation or pathway. Third, our study used a cross-sectional approach, meaning that we could only examine the impacts on academic performance at one point in time. If possible, future studies should utilize longitudinal data to examine these relationships over time. Additionally, we received a 30 percent response rate for the EPISD survey. Future studies could employ multimodal data collection designs in order to improve upon the response rate. Lastly, future studies should investigative air pollution, health status, and school performance in other metropolitan US cities as well as abroad to inform environmental justice oriented international policy decisions.

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