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Health Status and Residential Exposure to Air Toxics: What are the Effects on Children's Academic Achievement?

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Abstract

This paper examines the effects of children's subjective health status and exposure to residential environmental toxins on academic performance for the first time, while adjusting for school-level effects using generalized estimating equations. The analysis employs National Air Toxics Assessment (NATA) risk estimates and individual-level data collected through a mail survey. Results indicate that poorer subjective health status and higher levels of residential air toxins are statistically significantly associated with lower grade point averages, meaning that there is an independent effect of air pollution on children's academic achievement that cannot be explained poor caretaker-rated health alone.

Keywords

Environmental justice; children; academic performance; health status; National Air Toxics Assessment

1. Introduction

The impact of children's health status on academic achievement has been well studied but the findings have varied across health conditions such as asthma and obesity.^{1,2} Studies examining the relationship between children's subjective health status and academic achievement have consistently found that poorer health status is associated with worse academic achievement outcomes.^{3,4} When children are unhealthy, they may have more difficulty learning than their healthy counterparts and have poorer academic achievement outcomes.⁵

A critical limitation of these studies has been that they have not included the impacts of environmental toxins on children's academic achievement, which have been shown to be significant influences when examined at the school-level.^{6–11} Environmental justice researchers have hypothesized that exposure to pollutants can increase children's risk for respiratory illnesses and cause them to miss school more frequently, leading to lower levels of academic achievement.^{6,7} When children are continuously exposed to air toxics, their cognitive development may be delayed or impaired, resulting in lower grades and standardized test scores.¹² The strength of the association between air toxics and academic achievement measures aggregated to the level of the school 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 individual-level studies. Exposure to air toxics may also intensify the association between poor health and academic achievement. But because the school health and environmental justice literatures have remained largely separate, these hypotheses have yet to be investigated. To address this gap, we examine the association between health status, residential air toxics risk estimates and grade point averages (GPA) among a representative sample of 4th and 5th graders in El Paso, Texas.

2. Literature Review

While some studies of health and academic achievement have focused on specific health conditions, others have examined children's health using more holistic measures. Overall health is most often measured using a single-item subjective health status variable (with Likert-type response options ranging from "poor" to "excellent").^{3,4} Most recently, Le et al.³ 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.³ 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.⁴ found that by the third grade, better health status was significantly associated with higher academic achievement outcomes. When specific physical illnesses, such as asthma and obesity are studied, findings for the relationship with academic achievement have been less robust. The findings for subjective health status more consistently show an association between poor health and reduced academic achievement, which is why we employ that measure in this study.

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 academic performance. In one of the first studies to do so, Pastor et al.⁶ used United States 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. They found that the risk from air pollution exposure at schools negatively and statistically significantly predicted standardized test scores, adjusting for school demographics. In a follow up study

that included all public schools in California, Pastor et al.⁷ found that the general pattern observed in the LAUSD held for the rest of the state. Outside California, similar studies have been conducted in Baton Rouge, Louisiana schools, with similar significant findings.^{9,10}

In this paper we estimate how children's subjective health status and exposure to toxic air pollution impact their academic performance. The research questions and hypotheses are: (1) Does children's subjective health status, particularly poor health, negatively impact GPA, independent of relevant covariates? Based on prior studies, we hypothesize that children who have lower health status scores will have lower GPAs than their healthier peers. (2) Does residential exposure to air toxins significantly impact GPA, when accounting for children's health status? We hypothesize that air toxins will be a significant predictor of GPA, even after adjusting for the effects of health status. If this is the case, it implies that exposure to air pollution may influence children's school performance through a mechanism not captured by parents' ratings of children's subjective health status (i.e., effects on children's functioning that are imperceptible). However, if only health status significantly predicts GPA, it will suggest that the health mechanism responsible for worse academic performance is largely recognizable to parents (as reflected by their children's subjective health status ratings). (3) Does exposure to air toxics modify the association between children's health status and GPA? We hypothesize that negative association between residential air toxics and GPA will be stronger for children with worse health status because we think they may be more sensitive to the impacts of pollution due to poor health.

Building off 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 school level. Our student-level data 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 children's caretaker-rated subjective 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. Data and Methods

3.1 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 2011.¹³ The population is 81% Hispanic, compared to 17% of US population and 38% of the Texas population. El Paso has a high rate of poverty (24% in 2011) that is significantly greater than the national rate (16%).

Air quality is a major concern in El Paso. El Paso is rated among the highest of Texas cities for carbon monoxide levels¹¹ and is ranked eighth out of 277 metropolitan areas in the US for annual particulate pollution.¹⁴ 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 US Army Air Defense Artillery Center, thriving trucking and rail freight industries, and an expanding military base.

3.2 Data collection

Data were collected through a cross-sectional mail survey that was sent to all caretakers of fourth and fifth grade students in the El Paso Independent School District (EPISD) in 2012.¹⁵ EPISD is the 10th largest district in Texas and in 2012, there were over 64,000 students enrolled in the district across 94 campuses.

We used the Tailored Design Method to obtain the highest response rate possible for the survey.¹⁶ 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;^{17–20} our sample was generally representative of the demographics of EPISD fourth and fifth graders.

Information was gathered through the survey on the primary and secondary caretakers of the child; 83% of caretakers were mothers; 10% were fathers, 4% were grandparents, 1% were step-parents, and 1% were aunts/uncles. 57% of secondary caretakers were fathers, 24% were mothers, 6% grandparents, 10% step-parents, and 1% were aunts/uncles. Six children were excluded from this analysis because they lived outside of the county limits and three children were excluded because of unconventional home and alternative schooling arrangements. This left 1,895 children for analysis.

3.3 Variables

3.3.1 School Performance Outcome—We use 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 1. On average, children had a mean GPA of 3.3 (out of a 4.0) and 78.4% had a GPA above 3.0. While not a perfect comparison, this grade distribution follows the national pattern: 82.2% of students received either mostly As or mostly Bs in 2007.²¹

3.3.2 Health Status Variable—Children’s caretaker-rated subjective health status is measured using a survey question from the International Study of Asthma and Allergies in

Childhood 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). A dichotomized version of this measure has been used in previous studies.^{3,4} Subjective health status is a well-established measure for gathering information on people’s health; it exhibits reliability because both medical professionals and lay people share a general understanding of health.^{22,23} In our sample, 72.9% percent of caretakers said their children had excellent or very good health while 20.8% said their children had good health. These percentages are comparable to statistics for Texas and the US. According to the Data Resource Center for Child and Adolescent Health,²⁴ 82.0% of Texas caretakers and 84% of caretakers nationwide said their child had excellent or very good health; 14.2% of Texas caretakers and 12.7% of caretakers nationwide said their child had good health.

3.3.3 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.²⁵ Currently, NATA is the best secondary data source for spatially explicit characterization of air toxics risk exposure in US metropolitan areas.^{26–28} We used the results from the 2005 NATA because it was the most recent available dataset.

To calculate the estimates for respiratory and diesel particulate matter (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.²⁹ 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 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.³⁰

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.⁷ 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.³¹

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 acquired 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 previous research.²⁶ 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.

3.3.4 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.³² It is represented by (1) qualifying for free or reduced price meals (FRPM) at school.³³ We used this variable instead of poverty because it is a less conservative measure of socioeconomic disadvantage than is poverty. FRPM is 185% of the poverty line. A total of 60% percent of participating students qualified for FRPM.

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.³⁴ Mothers had about 13 years of education on average. 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 stimulating home environments.³⁴ 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.^{32,35} 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?" 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.³² Mother's English proficiency is treated as a continuous indicator and mothers had an average score of 2.17 for English proficiency, on a four point scale (0=not at all; 1=not well; 2=well; and 3=very well). 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. Both males and females were equally represented in the sample.

3.3.5 Schools—We control for clustering at the level of the school because the school context is a known influence on children's academic performance.⁸ 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 subjective 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); between 8 and 61 children attended each school.

3.4. 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.³⁶ We imputed missing values for multiple datasets ($n=20$) and specified 200 between-imputation iterations to ensure independence among the datasets.³⁷ MI techniques appropriately adjust the standard errors for missing data.³⁷ 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 equations (GEE) with robust covariance estimates. GEEs extend the generalized linear model³⁸ to accommodate non-normally distributed data that is correlated and provide a general method for the analyses of clustered variables.^{39,40} For this analysis, GEEs enable us to examine the associations between subjective health status, air toxics risk and GPA (all non-normally distributed variables), while accounting for school-level effects.

Because our focus is on population-averaged predictors of GPA, and not school effects, GEEs are appropriate because the intraclass correlation estimates are adjusted for as nuisance parameters and not modeled as in multilevel modeling approaches.⁴¹ Although other methodological approaches may account for the intraclass 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 intraclass 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 subjective health status on GPA, while controlling for the ten relevant covariates. 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).

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.⁴² 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 and selected gamma with log link because it had the lowest QIC for each of the models.

4. Results

4.1 Correlations

Correlations are presented in Table 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 ($p<.01$) were positively correlated with GPA.

4.2 Generalized Estimating Equation Results

In terms of the results for our first research question (see Table 3), child's caretaker-rated health status was positively and significantly associated with GPA, adjusting for relevant covariates. In terms of the control variables, 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.

To answer the second research question, air toxic variables were added to the model (see Table 3). Across both models, child's health status remained positively and statistically significant. In terms of the findings for the air toxics variables, both were significantly and negatively associated with GPA, controlling for the other variables. In terms of control variables, the findings were similar in terms of direction and significance as they were in model 1. To address the third research question, 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.

4.3 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.⁴³ Here, health status and the air toxics risk variables remained statistically significant for both boys and girls.

5. Discussion

The findings from this study serve to illustrate the importance of both subjective health status and exposure to air toxics on children's academic achievement. When studied separately, both pollution^{6,7,9,10} and caretaker-rated health status^{3,4} are known to be important predictors of academic achievement in childhood. There are multiple mechanisms by which children's health status can impact GPA. Being in poor health can influence cognition and ability to retain information learned in school and can increase absenteeism, all of which are negatively associated with GPA.⁵ 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 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.⁴⁴

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 parent-reported 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. 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,^{6,7} while studies on the health risks related to diesel PM are only beginning to appear in the literature.^{26,45} Diesel PM is associated with both acute and chronic health effects,⁴⁶ and 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 or vice versa;^{7,8} 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 others⁴⁷ have identified issues with the use of the subjective health status variable especially when surveys are collected in Spanish and English. Self-rated or caretaker-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.⁴⁷ 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 subjective health status 4.74 out of 6, while those who responded in English rated their children's subjective 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.

6. Conclusion

Poor academic performance at a young age can have lifelong impacts on a person's developmental trajectory and life chances. Among children with chronic health conditions, lower academic achievement outcomes have been linked to worse labor market outcomes and poorer health in adulthood.⁴⁴ 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 while adjusting for subjective health status. The results of this study also contribute to a broader understanding of the relationship between children's subjective health status and academic achievement. These findings provide another piece of evidence that should inform advocacy for pollution reduction in the US and beyond.

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Table 1

Descriptive statistics for all analysis variables

	N	Minimum	Maximum	Mean	SD	% Missing
GPA	1690	0.2	4	3.3	0.7	10.8
Child's subjective health status	1878	2	6	5.1	0.9	0.9
Total respiratory risk	1895	0.6	6.88	1.94	0.86	0
Total diesel PM risk	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

Table 2

Correlation Matrix

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

Note:

* p<.05,

** p<.01

Table 3

Results of the GEE Models Predicting Child's GPA

	Model 1		Model 2		Model 3	
	β	Sig.	β	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	0.098
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 subjective health status	0.035	0.000	0.034	0.000	0.034	0.000
Total Respiratory Risk	n/a	n/a	-0.023	0.004	n/a	n/a
Total Diesel PM Risk	n/a	n/a	n/a	n/a	-0.021	0.009

^aReference category is non-Hispanic white.