Birth Weight in Relation to Monitored Gaseous and Particulate Air Pollutants Assessed at the Neighborhood Level: Results from Five U.S. States

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ABSTRACT

Exposures to environmental hazards are thought to interact with stress to produce higher than expected disease rates in disadvantaged communities. In this study, I evaluated the relationship between preterm air pollutant exposure and birth weight and I investigated whether neighborhood-level poverty, representing a psychosocial stress indicator, modifies the effects of air pollution on birth weight. The following pollutants were analyzed in our study: SO_2, NO_2, CO, O_3, $PM_{2.5}$, PM_{10}, and PM_{coarse}. Data comes from California, Colorado, Georgia, Texas, and New Jersey. Air pollution data was joined to the birth certificate data by identifying the nearest operational air monitoring station to the centroid of a mother's census tract of residence. Small but significant negative effects of air pollutants on birthweight were found for all pollutants except for $SO_{2.}$ Gaseous pollutants are reported in pphm, with the exception of CO which is presented in ppm. Particulate matter pollutants are in 10 g/m^3. Effect sizes, reported as point estimates and 95% confidence intervals were as follows: CO, -2.88 (-4.19, -1.56); NO_2, -4.58 (-5.2, -3.96); O_3, -5.85 (-6.65, -5.04); SO_2 -1.01 (-3.81,1.79); PM_{10} -2.72 (-3.35, -2.09), PM_{25} -4.49 (-5.83, -3.14), PM_{coarse}-4.49 (-5.82,-3.16). The results indicate that air pollution may be just one of many factors that determine birth weight and that it often could be overshadowed by more important socioeconomic determinants. While the decreases in birth weights associated with expected exposure levels in the United States is unlikely to have clinical significance for a single child, there may be larger societal health or economic effects.

KEYWORDS

birth outcome, air pollution, poverty, ethnicity, socioeconomic status

INTRODUCTION

Environmental hazards are often associated with low-income neighborhoods and communities of color. Environmental justice, synonymous with this concept, is often traced to an important moment in the public realization of racial and social environmental health disparities: a study done by United Church of Christ in 1987 which explicitly demonstrated a clear racial divide between communities that contain toxic waste sites and those that do not (Taylor, 2000). Since then, much research describing spatial environmental injustices have primarily focused on the geographic proximity of communities of color to toxic sources, and the risks associated with this proximity (Pastor, Sadd, & Hipp, 2001). Following the steps of exposure assessment, more recent environmental justice research has shifted towards measuring individual-level exposure to ambient hazards in order to estimate the health effects of these exposures (Rachel Morello-Frosch & Shenassa, 2006).

Exposures to environmental hazards are thought to interact with stress to produce higher than expected disease rates in disadvantaged communities (Rachel Morello-Frosch & Shenassa, 2006). Several authors have focused on the so-called "double jeopardy" issue: neighborhoods found to have significant levels of pollution bear the additional burden of psychosocial stress and this stress could potentially modify the effects of pollution exposure on health outcomes (Clougherty & Kubzansky, 2009; Gee & Payne-Sturges, 2004; Morello-Frosch & Shenassa, 2006). Theories regarding this potential interaction are often based on the concept of allostatic load which leads to "weathering" (Geronimus, 1992). This theory states that cumulative lifetime exposure to stress can increase vulnerability to toxics and that total life stress is elevated for communities of color and the economically disenfranchised (Holzman et al., 2009; Spence & Eberstein, 2009). However, few studies have investigated whether exposure to air pollution specifically produces different health effects by socioeconomic status, factors that are often used as proxies to indicate community-level psychosocial stress (Clougherty & Kubzansky, 2009).

Negative birth outcomes are relevant factors on which to investigate the health disparities associated with air pollution, stress, and potential synergies between the two. Studies show that air pollutants are correlated with birth defects (Ritz et al., 2002) as well as preterm births (Ritz, Yu, Chapa, & Fruin, 2000). Perhaps the most frequently studied birth outcome is birth weight. Low birth weight has been linked to exposure to several different air pollutants such as particulate matter (Dejmek, Selevan, Benes, Solanskỳ, & Sram, 1999) and CO (B. Ritz et al., 2002). Despite the body of literature linking air pollution to poor birth outcomes, toxicological mechanisms for these outcomes are still largely unknown. What is known is that birth weight is a strong indicator of infant mortality, cognitive development, and long-term risk of heart disease (Barker, 1995; McCormick, 1985; Sorensen et al., 1997). Therefore, research into the association between environmental hazards and birth weight is worthwhile from policy-making and population-health perspectives. The association between birth weight, exposure to air pollution, and stress has only recently been studied (Morello-Frosch, et al., forthcoming), and results have been inconsistent. An interaction between community stressors and exposure to air pollution could mean that high-risk communities associated with environmental hazards and high levels of psychosocial stress not only receive greater health burdens from these factors individually, but that long-term congenital health burdens are potentiated by the interaction of these factors, thereby furthering a cycle of social and economic disempowerment.

In this study, I evaluate the relationship between preterm air pollutant exposure and birth weight. Additionally, I investigate whether a neighborhood-level stress indicators, specifically poverty, modifies the effects of air pollution on birth weight. Specifically, I will answer whether exposure to SO_2, NO_2, CO, O_3, $PM_{2.5}$, PM_{10}, and PM_{coarse} are significantly correlated with changes in birth weight. My study also aims to address the question of whether poverty interacts significantly with air pollutants to produce different health outcomes for different levels of neighborhood-level poverty. I hypothesize that there will be small but significant changes in birth weight for changes in concentration of ambient air pollutants and that these effects will differ by neighborhood poverty levels.

METHODS

Data coding

The data used in this study comes from three types of sources: tract-level census data, air quality monitoring stations, and state birth certificates. Geographically, the birth outcome, air quality, and census data are sourced from California, Georgia, Colorado, Texas, and New Jersey which are the states from which my advisors, Bill Jesdale and Rachel Morello-Frosch, were able to get birth certificate data that provide a sound representation of the geographic distribution of the country. Census and birth certificate data are joined by census tract. Census data includes neighborhood poverty (measured as the proportion of individuals below the poverty line), education, and unemployment levels. I converted these to categorical variables to avoid having to fit non-linear models. The information from the birth certificate dataset provided the outcome variable, birth weight, which was restricted from 1000 to 6000 grams. Additionally, infant sex, gestational age (restricted from 37 to 42 weeks) calendar year, and season of birth were included. Other covariates included were maternal birthplace, age, race, marital status, educational attainment, parity, month of first prenatal care, maternal presence/absence of hypertension, diabetes, herpes, and state of residence of the mother. All of these variables were coded as categorical data. Because some states did not collect information on certain variables, I designated all of the entries in the states with missing data as “not recorded.” Entries that were missing were coded as a separate level from variables which were not collected in a state. This allowed me to estimate separate effects for individuals who did not personally fill out the data, in case this was a non-random occurrence.

Exposure Assessment

The data I received from my advisors was joined the air pollution data to the birth certificate data by identifying the nearest operational air monitoring station to the centroid of a mother’s census tract of residence. For each pregnancy, my advisors estimated average exposure levels using the corresponding months of air quality data from the nearest operational monitoring station. If a monitoring station was non-functional for one week or more out of a month, the monitoring station was considered not operational for that period and the next nearest operational monitoring station was used to estimate exposures for the month of that pregnancy. Therefore, we used multiple monitoring stations to estimate exposure levels for some pregnancy.

We then measured the distance between the mother's residential census tract centroid and the farthest monitoring station used to estimate her exposure. This distance was then converted into 5 different binary variables, called "distance validity terms." These distance validity terms indicate whether the mother lived within 2km, 3km, 5km or 10km of the farthest monitoring station used to estimate her exposures. For example, if a woman lived exactly 2.5 km from the nearest operational monitoring station, the value of the 2 km distance validity term would be coded as "0" for that birth, indicating that this birth's exposure estimates are invalid at 2km. The remaining distance validity terms (3 km, 5km, 10km) would be coded as "1," indicating that this birth's exposure estimates are valid at the 3 km, 5 km, and 10 km distance levels.

To estimate exposures for each birth, we created monthly ambient pollution concentration averages, which we converted to trimesterly averages. Trimesterly averages were used to estimate an average for the overall pregnancy. Therefore, each pregnancy was associated with four exposure estimates for each pollutant—one for each pregnancy and a "full pregnancy" estimate.

Statistical Analysis

Multivariate linear models were used to estimate the effect of each air pollutant on birth weight. I used R version 2.11.1(R Development Core Team (, 2009) and Revolution Analytics suite version 4, particularly the RevoScale R (Revolution Analytics, 2011) package, to run the models.

To hold covariates constant between models, I ran each model with all births in the data set, regardless of distance level, but I estimated the effects of each pollutant specifically for births valid in the corresponding distance radius. In order to use all births for covariate effect estimates but to only use births near a monitoring station for air pollutant effect estimates, I interacted the exposure estimate with the distance validity term described above. The interaction between the pollutant exposure estimate and corresponding distance term (where the distance term indicated whether the woman lived within a specified radius of her nearest monitoring station), produced two separate coefficients, one for each level of the distance validity term. Where the validity term equaled 1, the effect estimate was interpreted as the effect of air pollution on birth weight for women who lived within the specified distance of a monitoring station. Where the validity term equaled 0, the effect estimate was interpreted as the effect of air pollution on birth weight for women who did not live within the specified distance—this effect estimate is therefore meaningless and was disregarded. I chose this method of interaction, rather than sub-setting the data for each model, because it held the values of the covariates constant across all permutations of all distance, trimester, and pollutant models.

I checked the assumptions of normality and constant variance using residual plots. For the continuous variables (pollutant levels), I checked the assumption of linear functional form.

Linear Models

The main results of this study, which determine the effects of air pollution on birth weight, came from linear models assessing the effect of each pollutant separately, at the 10 km distance level, and adjusting for all covariates. To address specific sub-questions and test assumptions, I also ran variations of these models for each pollutant. Initially, models with fewer covariates were tested. I also estimated the effects of pollutants on birth weight for women from each U.S. state separately. I estimated the effects at different distance levels, trimester-specific effects, "copollutant" effects (the effects of one pollutant after adjusting for the effects another pollutant), and the poverty interactive-effects.

I compared models with different sets of covariates included. The basic model included only sex, gestational age, one pollutant, and the maternal state of residence. In addition to controlling for the variables in the basic model, the individual-level model controlled for calendar year, season, maternal age, maternal race, birthplace of the mother, marital status, educational attainment, parity, month of first prenatal care, and a binary variable that indicated whether the mother presented with herpes, hypertension, or diabetes at the time of giving birth. The community-level model included all variables from the previous models as well as neighborhood poverty, owner occupation, education, and unemployment. Comparing models with successively more covariates allowed me to demonstrate how effect estimates were mitigated or increased as more variables were included, in order to investigate the possibility of collinearity. The community model was used to test significance levels and confidence intervals for the effects of the pollutants because this model controlled for the largest number of relevant covariates without a noticeable decline in degrees of freedom.

While a higher distance-level model has more samples and therefore higher power, the exposure assessment is associated with lower certainty. Running models with difference distance cutoffs allowed me to investigate how the pollution effect appeared to change as distance from monitoring stations increased. Inconsistent results across different distance-level models could indicate that higher distance models assume incorrect exposures. All models presented below used exposure data from women within 10 km of monitoring stations. However, I also analyzed and compared models with stricter distance cutoffs at 2, 3, and 5 km to assess the reliability of including the larger 10 km range. Results indicated that the 10 km estimates were consistent with estimates at stricter levels.

Estimating the effect estimate for each trimester allowed me to demonstrate which trimester of exposure had the strongest effect. In order to tease apart the unpredictable effects of collinear trimester estimates, I analyzed trimester-specific effects using two methods. First, the effect of each trimester was analyzed independently of the effects of the remaining trimesters—that is, each trimester-specific effect was estimated in its own “independent” model. Then, all three trimester-specific effects were analyzed together as different terms in a single, “grouped” model, thus producing a different set of trimester-specific effects. Results from the independent and grouped method were then compared for each trimester.

To estimate whether the effect of air pollution on birth weight is modified by poverty, I interacted the distance by pollution level with these covariates, separately. This produced effect estimates for each level of poverty.

RESULTS

Descriptive comparisons between states are presented to show that grouping data from multiple states is reasonable. Table 1 shows descriptive statistics for selected covariates by state. These descriptive statistics did not demonstrate major differences in the distributions of most covariates between states. Marital status was low in California due to a large percentage of missing data. Neighborhood poverty levels also differed considerably. Table 2 presents the distribution of birth weights by state with mean and standard deviation. Colorado had slightly lower birth weights but in general the distributions did not differ appreciably. Appendix Table 1 presents the distribution of each pollutant by state, indicating largely different distributions of air quality in each state.

Table 1. Descriptive Covariates by State. Most covariates are similarly distributed between states.

Variable	Level	California	Georgia	New Jersey	Colorado	Texas
Sex	Male	51%	51%	51%	51%	51%
Gestational age (wks)	37	6%	10%	7%	8%	8%
	38	14%	20%	18%	18%	20%
	39	27%	29%	27%	29%	29%
	40	28%	27%	35%	33%	32%
	41	18%	11%	11%	11%	8%
	42	7%	3%	2%	1%	2%
Age Group	15 to 19	9%	12%	8%	11%	14%
	20 to 34	74%	76%	75%	75%	75%
	35 to 49	16%	12%	17%	14%	11%
Race/Ethnicity of Mother	non-Hispanic Black	6%	34%	18%	4%	12%
	non-Hispanic Asian	13%	3%	6%	3%	4%
	Hispanic	50%	10%	25%	28%	47%
	non-Hispanic White	31%	52%	51%	64%	37%
Mothers Marital Status	Married at time of birth	15%	65%	69%	74%	69%
Education of Mother	7th to 11th Grade	29%	21%	17%	21%	32%
	4 or more years college	24%	28%	30%	31%	21%
	1-3 yrs college	20%	22%	20%	20%	17%
	High school or GED	27%	30%	33%	28%	29%
Previous Live Births	None	60%	57%	58%	57%	59%
Risk Factors	Present	5%	7%	9%	9%	9%
Neighborhood Poverty	Less than 5%	14%	7%	8%	3%	15%
	5% to 10%	18%	10%	13%	10%	20%
	10% to 20%	31%	28%	24%	26%	25%
	20% to 30%	22%	27%	20%	28%	19%
	30% or more	15%	27%	36%	34%	20%

Table 2. Median birth weight and interquartile range by state. Birth weights are comparable between states.

State	Median BW	IQR
California	3405	3118 to 3719
Colorado	3317	3033 to 3600
Georgia	3374	3090 to 3714
New Jersey	3410	3110 to 3727
Texas	3380	3091 to 3686

The results of linear models aggregated over all states for full pregnancy at the 10km distance are presented in Table 3. These effect estimates were adjusted for all inter-quartile range and indicated significant negative effects for all pollutants except for SO_2. Appendix Table 2 compares models that include increasing levels of covariates, broken down into "basic" (only sex, gestational age, state, and pollutant), "individual" (all additional characteristics specific to the mother) and "community" (all factors obtained from census data). Adding additional covariates decreased the size of exposure effect estimates, but they generally stayed significant and negative. The pollutant distributions provide context for interpreting biological meaning of the effect sizes; these distributions are presented in Table 4.

Table 3. Effect estimates, 95% confidence intervals, and P values by pollutant at the 10 km range adjusted for all covariates. All effect estimates are negative and significant with the exception of SO_2.The "estimates" column indicates the decrease in birth weight (in grams) per corresponding unit change in exposure.

	Estimate	95% CI		P
CO (ppm)	-2.88	-4.19	-1.56	0
NO_2 (pphm)	-4.58	-5.2	-3.96	0
O_3 (pphm)	-5.85	-6.65	-5.04	0
SO_2 (pphm)	-1.01	-3.81	1.79	0.479
PM_{10} (10 g/m_3)	-2.72	-3.35	-2.09	0
PM_{25} (10 g/m^3)	-4.49	-5.83	-3.14	0
PM_{coa}r (10 g/m^^{3})	-4.49	-5.82	-3.16	0

Table 4. Distribution of air pollutants. Mothers living at the 10 km range were used to calculate this table. The 1st and 3rd quartile is the amount of pollution that mothers in the 25th and 75th percentile of exposure experience on average. Therefore, this inter-quartile range ("IQR") encompasses average exposures of the middle 50% of the population. Using the effect estimates in Table 3, the IQR can be used to calculate a decrease in birth weight corresponding with a shift from the 1st quartile to the 3rd quartile.

	Median	1st Qu.	3rd Qu.
CO (ppm)	0.7	0.5	1.0
NO_2 (pphm)	2.1	1.6	2.9
O_3 (pphm)	2.3	2.0	2.7
SO_2 (pphm)	0.3	0.2	0.5
PM_{10} (10 g/m^3)	2.7	2.3	3.3
PM_{25} (10 g/m^3)	1.4	1.1	1.8
PM_{coar} (10 g/m^3)	1.5	1.2	2.0

Trimester-specific effects were estimated in independent models and in a grouped model. Table 5 shows only trimester-specific effects from independent models, meaning that for these results I did not adjust the effects of each trimester for the for the effects of the remaining trimesters. Qualitative differences indicated decreased effects of CO, NO_2, and PM_{25} in the second trimester as compared to the first and third. PM_{10} showed larger effects later in pregnancy, and SO_2 remained non-significant for all trimesters.

Table 5. Trimester-specific Effect Estimates. This table presents effect estimate for each trimester of pregnancy. Estimates were analyzed in independent models.

	CO				**NO2**			
	Estimate	**95% Conf. Int.**		**P**	**Estimate**	**95% Conf. Int.**		**P**
Tri 1	-2.75	-3.89	-1.62	0	-4.27	-4.83	-3.71	0
Tri 2	-1.26	-2.35	-0.18	0.023	-3.33	-3.86	-2.8	0
Tri 3	-3.82	-4.92	-2.71	0	-4.46	-4.99	-3.93	0
Full Preg	**-2.88**	**-4.19**	**-1.56**	**0**	**-4.58**	**-5.2**	**-3.96**	**0**
	O3				**SO2**			
	Estimate	**95% Conf. Int.**		**P**	**Estimate**	**95% Conf. Int.**		**P**
Tri 1	-3.18	-3.77	-2.59	0	-0.92	-3.54	1.7	0.49
Tri 2	-3.36	-3.9	-2.81	0	0.4	-1.95	2.76	0.737
Tri 3	-2.3	-2.84	-1.77	0	0.75	-1.62	3.12	0.535
Full Preg	**-5.85**	**-6.65**	**-5.04**	**0**	**-1.01**	**-3.81**	**1.79**	**0.479**
	PM10				**PM25**			
	Estimate	**95% Conf. Int.**		**P**	**Estimate**	**95% Conf. Int.**		**P**
Tri 1	-1.75	-2.24	-1.26	0	-3.57	-4.62	-2.52	0
Tri 2	-2.31	-2.77	-1.84	0	-2.59	-3.54	-1.63	0
Tri 3	-3.05	-3.51	-2.58	0	-3.44	-4.39	-2.49	0
Full Preg	**-2.72**	**-3.35**	**-2.09**	**0**	**-4.49**	**-5.83**	**-3.14**	**0**
	PMcoar							
	Estimate	**95% Conf. Int.**		**P**				
Tri 1	-4.01	-5.05	-2.97	0				
Tri 2	-3.84	-4.75	-2.93	0				
Tri 3	-4.34	-5.24	-3.45	0				

Full Preg	**-4.49**	**-5.82**	**-3.16**	**0**

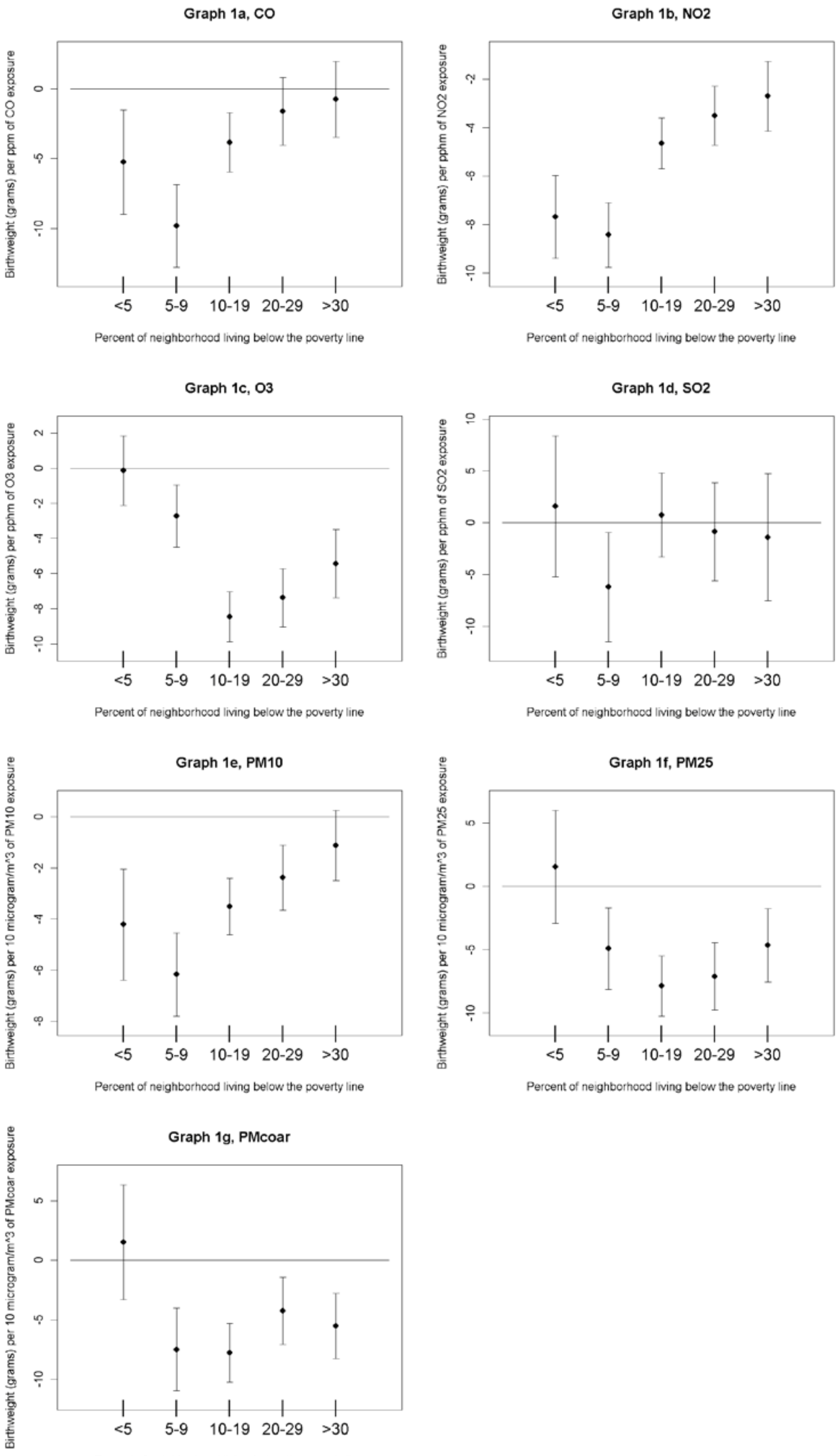
Copollutant models were evaluated but the results are not presented in this paper due to their size limited interpretability. The effects of each pollutant were estimated in six additional models, each adjusting for a different co-pollutant. Effect estimates remained the same in copollutant models with the exception of some highly correlated pollutants and other pollutants, notably NO_2 and CO. CO and NO_2 both had radically different effect estimates after adjusting for the other. CO and O_3 estimates also changed after the inclusion of the other copollutant. Correlation of exposures by air pollutant are demonstrated in the correlation matrix in Table 6. Only PM_{10} shows high correlation with the other PM pollutants.

Table 6. Correlation Matrix of Pollutants, R^2 values.

	CO	**NO2**	**O3**	**SO2**	**PM10**	**PM25**
CO						
NO2	0.20					
O3	0.19	0.15				
SO2	0.23	0.00	0.07			
PM10	0.05	0.15	0.01	0.00		
PM25	0.31	0.38	0.06	0.00	0.44	
PMcoar	0.00	0.01	0.08	0.01	0.60	0.06

Poverty-specific estimates were found by interacting the poverty term by exposure. These represent the effect modification of poverty on air pollution by birth weight. Figures 1a through 1g show the effect of air pollution on birth weight estimated separately for each poverty level. For pollutants CO, NO_2, and PM_{10}, the effect of air pollution on birth weight was less negative for higher levels of community-measured poverty rates. O_3 and PM_{25} appeared to have parabolic shapes where individuals living in low and high poverty neighborhoods experienced less negative effect size compared to those living in middle poverty neighborhoods. Poverty-specific effects of SO_2 and PM_{coarse} showed no clear pattern.

Figures 1a-1g. Poverty-Specific Effects of Exposure on Birth Weight, adjusted for all covariates, 10km.



DISCUSSION

Many studies have investigated the effect of air pollution on birth weight, but few have incorporated data from such a large geographic region or sample size. Additionally, few studies have attempted to address the question of whether the effect of air pollution on birth weight is modified by the effects of poverty. This study aimed to determine the effect of air pollution on birth weight across a large area and to investigate the whether this effect varies by socioeconomic status. The merged state results are consistent with previous research that shows a small, but significant negative effect of air pollution on birth weight (R. Morello-Frosch, Jesdale, Sadd, & Pastor, 2010; Beate Ritz & Wilhelm, 2008).

As indicated by the pollutant distributions in Table 4, the effect estimates presented in Table 3 are quite small. For example, 50% of exposed mothers experience an average range of .5 to 1 ppm of CO over her pregnancy. The effect estimate is -2.88 g/ppm, meaning that shifting from the 25th percentile of exposure to the 75th percentile of exposure would only decrease birth weight by about 1.44 grams. NO_2 has the largest biological effect when considering exposure, but even then a shift from the 25th percentile to the 75th percentile of exposure would only yield a 6 gram decrease in birth weight. These small effect sizes indicate that the effect of air pollution on birth weight is overshadowed by factors with larger determinants. Nevertheless, the results are significant after controlling for potential confounders (excepting SO_2), indicating that these pollutants may have some true association with fetal development.

Merging data from different states

The descriptive statistics comparing data from different states address the question of whether merging the disparate state data sets is justifiable. Comparative covariate statistics indicate that covariates are relatively similar between states. Distribution of neighborhood poverty-level, however, which varies by state, might have an effect on the poverty interaction. Similarly, birth weight distributions are nearly identical. Air pollution distributions, on the other hand, vary greatly between states. These distributions are presented in Table 1 of the Appendix and show that not only do pollutants have different medians, but that states have such varying ranges that some distributions in different states barely overlap. This is problematic because the model assumes a linear dose response. If the dose-response were not truly linear, then the assumption of a constant slope across the range of exposures patched together from different data sets would not be valid. Additionally, the data from states at the far ends of the distribution ranges are likely to act as leverage points, causing data from some states to contribute more to the slope estimate than data from other states.

Although not presented here, I assessed the consistency of the results between states by running individual state models and comparing the results to the merged state model. Results were consistent for CO, NO_2, and O_3, except for in Georgia where effect size was estimated to be much greater (likely due to seasonally-dependent monitoring practices in this state). The effects of PM_{10} were not consistent across states. These inconsistencies could be the result of different distributions of pollutant exposures among the different states. Different standard deviations or IQRs in air pollution exposure in different states could cause changes in the absolute magnitude of the effect sizes (although this does not explain the positive significant effects observed for PM_{10} in some states). Since states have different distributions and different average doses, the assumption of a linear dose response could be implicated in these inconsistent results.

Further analysis might warrant analyzing exposure as a categorical variable to avoid the assumption of linear dose response. Despite the complexities in reporting and analyzing the data, running the analysis categorically would eliminate issues with linear dose response and would not rely on a single estimate across the full distribution of exposure which is essentially a patchwork of different states. Despite these concerns, for the purpose of this paper I have grouped the data.

Trimester-Specific Estimates

The justification for estimating trimester-specific effects is that environmental exposures in specific trimesters can have a disproportionate effect on birth weight compared to other trimesters. Smoking and alcohol consumption are well known to have the largest effect in the first and second trimesters (Chatenoud et al., 1998; Harlap & Shiono, 1980;

Spencer, 1999). The difficulty with assessing trimester-specific effects, however, is that exposures in any given semester are often highly correlated with exposures in the remaining trimesters. This problem of collinearity makes trimester-specific estimates unreliable because highly collinear variables respond erratically to minor, random differences in the data. Nevertheless, previous studies on air pollution and birth weight have estimated trimester-specific effects (Bell, Ebisu, & Belanger, 2007; Mannes et al., 2005), often using sensitivity tests to attempt to determine true differences between trimesters.

The results presented above, which show slightly less negative effects for the second trimester of CO, NO_2, and PM_{25} and larger effects later in pregnancy for PM_{10}, do not necessarily indicate true differences in trimester effects because no significance test was done to compare estimates. Higher correlations between trimesters 1 and 2 and between trimesters 2 and 3 compared to trimesters 1 and 3 could cause the apparent reduced second trimester effect for some pollutants. This trend becomes more pronounced in models where all trimester estimates are included in a single analysis; for some pollutants trimester 2 estimates become positive and significant, indicating that collinearity could be causing the decreased second-trimester trend. Any inferences drawn about true differences in trimester effects from this study are not conclusive. To better answer the question of trimester-specific effects, a study would need to be designed specifically with this question in mind in order to address the issue of collinearity.

Copollutant models

The effect of most pollutant remained robust to the inclusion of additional pollutants in the model. As expected, the highly collinear particulate matter pollutants demonstrated unreliable effect estimates after adjusting for other particulate matter pollutants. However, the pollutants CO and NO_2 demonstrated unreliable changes in exposure estimates, despite their low R^2 value. For example, the effect of CO becomes significant and positive after adjusting for NO_2. Similarly, the estimate for O_3 adjusted for NO_2 (and visa versa) became nearly twice as strong even with an R^2 valu as low as .24. Hypothetically, this could indicate that only one of O_3 or NO_2 are actually causing decreased birth weight and that the remaining pollutant is demonstrating an unadjusted effect due to a small amount of collinearity (and similarly for CO and NO_2). However, the correlation values as demonstrated in correlation matrix (Table 6) are so small that they cannot entirely explain the unpredictable effect estimate changes. Alternatively, the unpredictable copollutant results could be the results of non-linear dose-response. Regardless, this behavior warrants further investigation.

Poverty interactions

The estimates of how poverty modifies the effect of air pollution on birth weight, as presented in Figures 1a through 1g, indicate that as poverty increases, CO, NO_2 and PM_{10} have decreasing effects on birth. These results counter theories of "weathering," which hold that as psychosocial stress increases, susceptibility to environmental hazard also increases (Gee & Payne-Sturges, 2004; Geronimus, 1992). A possible explanation is that the effect of stressors (be they environmental or social) on birth weights diminishes for increased exposure to stressors. Neighborhood-level poverty alone has a large negative effect on birth weight (Buka, Brennan, Rich-Edwards, Raudenbush, & Earls, 2003). This effect could be potentially so large that it overwhelms the effect of air pollution on birth weight. Theoretically, impoverished individuals may have already experienced a decrease in birthweight large enough to overwhelm the biological pathways through which air pollution might otherwise decrease birthweight for a less impoverished person.

An alternate explanation of the apparent diminishing effects of air pollution for increasing poverty levels is that these results stem from inconsistencies in the data. Table 1 shows that poverty levels are not completely consistent between states. Combining this inconsistency with the fact that the range of exposures are different between states could cause unexpected results when testing the interaction between air pollution and poverty.

Limitations

Although I controlled for several covariates in my model, I was unable to obtain maternal smoking data which could have altered the conclusions. The effects of smoking on birth weight are clear (General, 1982), although one study on the association between PM and birth weight in Arizona and Florida found that effects of PM on birth weight were only slightly altered after including maternal smoking in the model, indicating that maternal smoking does not confound the relationship between PM exposure and birth weight (Basu, 2003).

Air pollution can vary greatly at neighbor-hood scales. Unfortunately, my analysis was limited by the granularity of air quality monitoring station placement and census tract locations on the mother's birth certificate (rather than actual home addresses). Furthermore, the analysis did not take into account the decreasing certainty of exposure assessments for women living farther from monitoring stations. This means that effect estimates might be less certain than the statistical 95% confidence intervals and p values actually indicate.

Attempts to estimate trimester-specific effects were limited by collinearity of trimester exposure data. Since correlation between trimester-specific estimates were as high as 60% for some pollutants, this indicated that drawing conclusions about any specific trimester was unreliable. The most I could conclude was that one, two, or all trimesters have an effect (if the full pregnancy estimate was significant) without knowing which trimester was the true cause of the apparent affect.

Additionally, the self-reported addresses on the birth certificates may not reflect where the mothers actually lived during pregnancy. More importantly, ambient air pollution levels in the zip code of residence do not necessarily reflect the air that an individual spends most of their time breathing. Outdoor ambient air pollution levels are not always reflective of indoor air pollution levels. There could be further differential measurement error due to different levels of outdoor to indoor seepage between impoverished and non-impoverished individuals. Despite very rough methods of exposure assessment, the significant negative results could indicate that a more accurate exposure assessment might find higher effects for breathing-level estimates.

Further research

As stated in the limitations section, the study did not address the issue of decreasing certainty of exposure assessment at higher distance-levels. Further studies on this topic should strive to achieve more accurate exposure assessment using breathing-level measurements. Alternatively, a novel study method could use existing data on the variability of ambient air pollutants to estimate uncertainty of exposure assessments and subsequently incorporate this uncertainty into an analysis similar to the one presented in this paper.

Additionally, further research needs to be done on the question of effect modification by psychosocial stress. For this study, I used the psychosocial socioeconomic indicator of neighborhood poverty as a proxy for psychosocial stress. A better approach would be to test the effect modification of air pollution by self-assessed stress levels, which have been shown to have a significant effect on birth weight (Wadhwa, Sandman, Porto, Dunkel-Schetter, & Garite, 1993).

Broader implications and conclusions

This study presents the effects of air pollution on birth weight in the context of a multi-state dataset. Currently there is no standardized method for collecting data on birth certificates which makes this type of multi-state study problematic. Nevertheless, the goal of seeking data from a larger geographic region is a worthy one. Focusing on the effects of air pollution in a single city or municipal area ignores variation of such effects across the United States.

This study indicates small but significant associations between exposure to several air pollutants and birth weight. While the terms “effects” and “effect sizes” have been used in this study, it is important to state that as an observational study, these results alone cannot establish causality. While this study does replicate the results of previous studies of air pollution exposure on birth weight, only a combination of repeatability, animal studies, and biologic plausibility can indicate causality. Even so, if these results do indicate the possibility of causality, whether a child’s birth weight being decreased by a few grams has any clinical relevance to that child is highly questionable. Nevertheless, ambient air pollution exposure levels in many countries outside of the United States are much higher. And if a linear dose response relationship holds, this could indicate that in areas of the world with higher ambient air pollution levels would result in large and clinically relevant decreases in birth weight. The results of this study cannot legitimately be extended beyond of this study’s sampling area and exposure levels, but further studies in highly polluted urban areas may be warranted by this study.

Although the decreases in birth weight associated with ambient exposure levels in the United States are unlikely to affect an individual child's health, there may be larger societal health effects. For example, cognitive development delayed by decreased birth weight might be depressed such that a population's average IQ is lowered, similar to effects of lead exposure (Schwartz, 1994). This theory is supported by the fact that even marginal changes in birth weight have been shown to predict changes in cognitive development in children (Matte, Bresnahan, Begg, & Susser, 2001). Marginal delays in an individual's cognitive development would likely have no significance to an individual, but the wide breadth of air pollution exposure could mean that wide-spread decreases in intelligence might have societal consequences. Furthermore, birth weight is a good indicator of overall health, and even small decreases in birth weight are associated with increased risks of several diseases. Therefore, the societal effect of decreased birth weight hypothetically due to air pollution would not be limited to just cognitive development. Decreases in societal health and well-being aggregated across the multiple outcomes of birth weight mean that marginal changes in birth weight may not be completely meaningless.

Nevertheless, despite potential population-level effects, the study results presented here indicate that air pollution is at most a small part of the many factors which determine birth weigh and that arguably more important socioeconomic determinants of health such as neighborhood poverty overshadow the effects of ambient air pollution exposure. Therefore, further research efforts investigating the effects of air pollution on birth weight might be most effectively applied in regions with higher ambient concentrations or where more accurate exposure assessment can be obtained.

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APPENDIX

Table 1. Distribution of Air pollutants by state.

State	Median	IQR
CO		
California	0.54	0.54 to 1.02
Colorado	0.61	0.61 to 0.91
Georgia	0.67	0.67 to 0.91
New Jersey	0.77	0.77 to 1.32
Texas	0.4	0.4 to 0.78
NO_2		

California	16.93	16.93 to 30.35
Colorado	17.28	17.28 to 33.55
Georgia	15.37	15.37 to 21.43
New Jersey	22.59	22.59 to 33.49
Texas	12.7	12.7 to 19.15
O_3		
California	19.09	19.09 to 27.26
Colorado	18.85	18.85 to 27.48
Georgia	25.46	25.46 to 28.36
New Jersey	17.27	17.27 to 24.85
Texas	22.08	22.08 to 27.76
SO_2		
California	1.23	1.23 to 2.82
Colorado	2.18	2.18 to 4.18
Georgia	2.91	2.91 to 4.33
New Jersey	5.08	5.08 to 9.39
Texas	1.26	1.26 to 3.75
PM_{10}		
California	23.3	23.3 to 38.23
Colorado	19.81	19.81 to 27.98
Georgia	22.87	22.87 to 29.25
New Jersey	26.87	26.87 to 33.56
Texas	21.91	21.91 to 30
PM_{25}		
California	11.89	11.89 to 20.52
Colorado	7.89	7.89 to 10.3
Georgia	14.89	14.89 to 18.16
New Jersey	13.12	13.12 to 15.17
Texas	10.59	10.59 to 12.94
PM_{coar}		
California	11.7	11.7 to 18.32
Colorado	15.41	15.41 to 23.64
Georgia	7.32	7.32 to 11.71
New Jersey	8.87	8.87 to 13.46
Texas	13.72	13.72 to 23.94

Table 2. Effect of Air pollution on Birth Weight Adjusted for Different Covariates. The basic model included only sex, gestational age, one pollutant, and the maternal state of residence. In addition to controlling for the variables in the basic model, the individual-level model controlled for calendar year, season, maternal age, maternal race, birthplace of the mother, marital status, educational attainment, parity, month of first prenatal care, and a binary variable that indicated whether the mother presented with herpes, hypertension, or diabetes at the time of giving birth. The community-level model included all variables from the previous models as well as neighborhood poverty, owner occupation, education, and unemployment.

	CO (ppm)				**NO_2 (pphm)**			
	Estimate	**95% CI**		**P**	**Estimate**	**95% CI**		**P**
Basic	-14.21	-15.4	-13.02	0	-11.1	-11.69	-10.51	0

Individual	-5.3	-6.6	-4.01	0	-6.54	-7.15	-5.94	0
Community	-2.88	-4.19	-1.56	0	-4.58	-5.2	-3.96	0

	O_3 (pphm)				**SO_2 (pphm)**			
	Estimate	**95% CI**		**P**	**Estimate**	**95% CI**		**P**
Basic	9.48	8.7	10.25	0	-77.6	-80.18	-75.02	0
Individual	-4.19	-4.98	-3.39	0	-5.06	-7.83	-2.29	0
Community	-5.85	-6.65	-5.04	0	-1.01	-3.81	1.79	0.479

	PM_{10} (10 g/m^3)				**PM_{25} (10 g/m3)**			
	Estimate	**95% CI**		**P**	**Estimate**	**95% CI**		**P**
Basic	-6.2	-6.82	-5.57	0	-7.36	-8.67	-6.05	0
Individual	-4.72	-5.34	-4.1	0	-8.84	-10.17	-7.51	0
Community	-2.72	-3.35	-2.09	0	-4.49	-5.83	-3.14	0

	PM_{coar} (10 g/m^3)			
	Estimate	**95% CI**		**P**
Basic	-4.81	-6.16	-3.46	0
Individual	-7.02	-8.35	-5.7	0
Community	-4.49	-5.82	-3.16	0