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Decomposition Analysis of Black–White Disparities in Birth Outcomes: The Relative Contribution of Air Pollution and Social Factors in California

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Background: Racial/ethnic disparities in preterm birth (PTB) are well documented in the epidemiological literature, but little is known about the relative contribution of different social and environmental determinants of such disparities in birth outcome. Furthermore, increased focus has recently turned toward modifiable aspects of the environment, including physical characteristics, such as neighborhood air pollution, to reduce disparities in birth outcomes.

Objectives: To apply decomposition methods to understand disparities in preterm birth (PTB) prevalence between births of non-Hispanic black individuals and births of non-Hispanic white individuals in California, according to individual demographics, neighborhood socioeconomic environment, and neighborhood air pollution.

Methods: We used all live singleton births in California spanning 2005 to 2010 and estimated PTBs and other adverse birth outcomes for infants borne by non-Hispanic black mothers and white mothers. To compare individual-level, neighborhood-level, and air pollution [Particulate Matter, 2.5 micrometers or less ($PM_{2.5}$) and nitrogen dioxide (NO_2)] predictors, we conducted a nonlinear extension of the Blinder–Oaxaca method to decompose racial/ethnic disparities in PTB.

Results: The predicted differences in probability of PTB between black and white infants was 0.056 (95% CI: 0.054, 0.058). All included predictors explained 37.8% of the black–white disparity. Overall, individual (17.5% for PTB) and neighborhood-level variables (16.1% for PTB) explained a greater proportion of the black–white difference in birth outcomes than air pollution (5.7% for PTB).

Conclusions: Our results suggest that, although the role of individual and neighborhood factors remains prevailing in explaining black–white differences in birth outcomes, the individual contribution of $PM_{2.5}$ is comparable in magnitude to any single individual- or neighborhood-level factor. https://doi.org/10.1289/EHP490

Introduction

Infants born to non-Hispanic black mothers show a much higher prevalence of preterm birth (PTB; delivered <37 weeks of gestation) relative to infants born to non-Hispanic white mothers in the U.S. (Braveman et al. 2015; McKinnon et al. 2016). In California, where more births occur than in any other state in the U.S. (Murphy et al. 2015), 12.8% of births to black mothers between 2003 and 2010 were preterm in comparison with 7.4% births to white mothers (Braveman et al. 2015). PTB serves as a key antecedent of neonatal mortality (Braveman et al. 2015; Lu et al. 2010), and health and developmental deficits throughout life (Saigal and Doyle 2008; Moster et al. 2008). For this reason, reducing PTB disparities may reduce lifelong black–white health disparities in the United States.

Although numerous studies identify a variety of individual maternal characteristics (e.g., education, age, and socioeconomic status) as potential explanations for this racial disparity in PTB (Blumenshine et al. 2010; lorch and Enlow 2015), clinical interventions (e.g., screening and referral for smoking, substance use, or poor nutrition) to reduce black–white disparities (Lu et al. 2010) or to specifically reduce PTB among black mothers have been thus far equivocal at best (Butler and Behrman 2007). For this reason, increased focus has recently turned toward modifiable aspects of the environment, including physical characteristics such as neighborhood air pollution (Burris et al. 2011; Shah 2010; Arroyo et al. 2016; Green et al. 2015), to reduce disparities in PTB.

Studies often acknowledge that disparities arise from a number of social and environmental factors (Braveman et al. 2015; Lorch and Enlow 2015), of which most are unmeasured (Schempf et al. 2011). However, few studies attempt to assess the contributions of major explanatory variables while simultaneously accounting for some unmeasured factors using fixed effects (Kaufman 2008). This gap in research limits the ability to identify and prioritize potential nonclinical interventions and limits our understanding of the relative contribution of social and physical environmental factors as they produce disparities. To address this issue, our study decomposes the difference (disparity) in PTB prevalence observed in the births of non-Hispanic black and non-Hispanic white infants. We partition this PTB disparity into several relevant predictors, including individual demographics, neighborhood socioeconomic environment, and neighborhood air pollution. We examined multiple factors that contribute to the black–white disparity in PTB in California births from 2005–2010. This analysis highlights the potential contribution of interventions aimed at reducing air pollution levels and to propose alternative strategies to reduce racial/ethnic disparities in birth outcomes.

Our decomposition analysis improves on existing work in several important ways. First, we focus on policy-relevant, modifiable, physical environmental factors (e.g., transit corridors) and account for nonmodifiable factors (e.g., age). This focus facilitates clear interpretation of results for public-health intervention and policy. Second, our methods make explicit the fact that much of the black–white disparity in PTB remains unexplained by measured factors. Third, we investigate related black–white

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disparities in other birth outcomes including birth weight, intrauterine growth, very preterm birth (VPTB), and small for gestational age (SGA) (Lorch and Enlow 2015). Fourth, we take advantage of a unique data linkage among individual natality files, neighborhood socioeconomic and demographic data, and objectively measured environmental data for the population base of births in California. The overall objective of this research is to apply decomposition methods to understand disparities in various birth outcomes' prevalence found between non-Hispanic black and non-Hispanic white births in California, according to individual demographics, neighborhood socioeconomic environment, and neighborhood air pollution.

Methods

We acquired data for all live singleton births in California spanning 2005 to 2010 from the natality file of the California Department of Health Services. The reporting of births in California is nearly 100% complete; the quality and provenance of the data are described elsewhere (Birth Cohort File 2015). The California Department of Vital Statistics performs several quality-control checks to ensure the validity of these and other variables on birth certificates. An important aspect is that the birth file contains maternal zip code of residence, which permits linkage of physical and social environment variables (described below). The State of California and the University of California, Irvine approved the study (IRB protocol approval #13-06-1,251 and 2013–9716, respectively).

Birth Outcomes

We focused our analysis on PTB, categorized as binary (yes/no). We did not include observations with missing gestational age, missing exposure (see below), or missing zip code information. Given documented black–white disparities in other related birth outcomes, however, we explored two additional, clinically meaningful outcomes: very-preterm birth $(\text{VPTB}) =$ delivery of an infant at between 20 and 33 completed weeks of gestation (yes/no); small for gestational age $(\text{SGA}) =$ sex-specific, birth weight $<$10th percentile for the given gestational age (yes, no).

Race/Ethnicity

We analyzed mothers who were identified as non-Hispanic black or non-Hispanic white. To be consistent with earlier literature, we did not consider fathers' race or ethnicity (Lhila and Long 2012; Lorch and Enlow 2012). Identification of maternal race or ethnicity was based on self-report.

Individual-level (Maternal) Predictors of PTB

We included the following maternal characteristics: *a*) age (linear and categorized as <20, 20–24, 25–29, 30–34, ≥35: considering 25–29 as reference group); *b*) educational attainment (<high school (HS), HS graduate or equivalent diploma, any college); *c*) Medicaid insurance status (yes/no); and *d*) indicator of missing paternal information status representing possibly single parenthood (Tan et al. 2004). We also recorded infant birth order (i.e., maternal parity) and infant sex given their documented relation with the outcomes of interest.

Neighborhood-level Predictors of PTB

Given the role of the socioeconomic environment as a key determinant of health disparities, we used 2010 Census information, gathered at the zip code level, as a measure of neighborhood context. We linked census data to the natality file by the zip code of mother's residence at the time of birth. The following socioeconomic environment variables, consistent with earlier work (Cushing et al. 2015), were included: *i*) proportion of the population over the age of 16 that is unemployed but eligible for the labor force; *ii*) proportion of the population over 25 with less than a high school education; *iii*) proportion of the population living below the federal poverty level; and *iv*) proportion of households in which no one 14 years old and over speaks English "very well" or speaks English only. We included all four census variables (classified into tertiles: low/middle/high) in the final models. In addition, we developed an alternative composite index of neighborhood socioeconomic environment that includes the same four variables but in a single continuous index stratified in three groups. We followed a similar approach as developed elsewhere (Meijer et al. 2013; Lalloué et al. 2013), mixing a principal component analysis (PCA) and ascendant hierarchical analysis. Hierarchical analysis is a method of clustering that creates a hierarchy of categories (i.e., clusters), frequently used after a PCA. We thus gathered zip codes in three homogenous socioeconomic categories numbered from 1 (the most privileged) to 3 (the most deprived).

Air Pollution Predictors

We used data provided by the U.S. Environmental Protection Agency (EPA) and the California Air Resources Board (CARB) to assign chronic air pollution (Mendola et al. 2016) exposures to each birth record, linked by maternal zip code of residence (Green et al. 2015; Wu et al. 2009). Air pollution measures were averaged annual concentrations across the entire study period (2005–2010) for each zip code, based on measurements from the nearest monitoring station. We included two pollutants: *i*) particulate matter ($PM_{2.5}$) (in $\mu g/m3$); and *ii*) nitrogen dioxide (NO_2) (in ppm). We chose these two types of air pollution given that their concentrations remain relatively stable over time but vary substantially across zip codes, and that they have strong documented relation with PTB (Burris et al. 2011; Mendola et al. 2016; Salam et al. 2005; Huynh et al. 2006; Stieb et al. 2012; Zhu et al. 2015). Nitrogen oxide species are the best available indicators of spatial variation in exposure to the outdoor urban air pollutant mixture (Levy et al. 2014). Air pollution variables were classified into tertiles (low/middle/high) for analyses. We also assessed sensitivity of findings to alternative classifications of the environmental factors (e.g., continuous), but inference remained essentially the same (see supplemental material).

Statistical Analyses

Quantifying Black–White Disparities

We first quantified black–white disparities for each birth outcome separately by estimating absolute and relative differences in the occurrence of our three outcome measures among all live singleton births in California between 2005 and 2010. Specifically, we used multi-level logistic regression with random intercepts to estimate marginal risk ratios (RR) and risk differences (RD) comparing non-Hispanic black mothers to non-Hispanic white mothers. To estimate RR and RD, we calculated average marginal effects (AME), which represents the change in the conditional mean of the outcome per unit change in exposure conditional on the covariates (Williams 2012). We also calculated Intra Class Correlations (ICC) for each outcome based on an estimator from a random intercept logistic regression model (Wu et al. 2012).

Next, we conducted similar analyses modeling the association between: *i*) individual-level variables, *ii*) neighborhood-level variables, and *iii*) air pollution exposure to the three birth outcomes.

The Blinder–Oaxaca Decomposition Analysis

To investigate the relative contribution of each of the considered factors, we conducted an Blinder–Oaxaca decomposition analysis (OBDA) (Oaxaca 1973; O'Donnell et al. 2008), a technique previously used to explain gender and race differences in wage rates. The OBDA has been recently applied to health-disparities research (Sen 2014). Briefly, the main goal of OBDA is to explain the "gap" in the modeled means of an outcome variable between two groups (here between PTB prevalence of non-Hispanic black and white mothers) by a set of predictors. OBDA partitions the gap into an "explained" portion and an "unexplained" portion (Sen 2014). The "explained" portion of this gap is the difference in the outcome attributable to group differences in levels of potential contributing variables. In this study, therefore, the "explained" portion represents the amount by which the black–white difference in PTB would be reduced in the hypothetical world where, other things equal, black mothers experienced the same mean levels of measured individual, social, and air pollution exposures as white mothers.

For PTB, we used a nonlinear extension (logit link function) of the Blinder–Oaxaca method. For each outcome, we estimated the difference in mean predicted probability of the outcome between black and white mothers and the relative contribution of each of the measured exposures (i.e., individual, social neighborhood, and air pollution predictors) to this difference. The variables were entered sequentially into the decomposition procedure for each category of exposure (i.e., individual, neighborhood and air pollution categories). Models that assessed the roles of neighborhood factors were adjusted for individual factors, and models that assessed the role of air pollution factors were adjusted for both individual and neighborhood factors. As the number of related exposures in each category of exposure differed (i.e., four individual-level exposures, four neighborhood-level exposures, and two air pollution exposures), we assessed whether the overall contribution of groups of variables were modified if only two individual-level exposures and two neighborhood-level exposures were included (different configurations were tested). However, by doing so, we did not observe changes in the overall contribution of air pollution exposures. We used a similar approach for the two other birth outcomes that have been examined separately (VPTB and SGA).

To account for the statistical nonindependence of birth outcomes in a neighborhood (i.e., clustering), we conducted multilevel OBDA in which women were nested in their zip codes of residence by using the cluster option in the *Oaxaca* command as presented by Jann (2008). All the analyses were conducted using Stata SE 14.1 (StataCorp, College Station, TX).

Results

Descriptive Statistics

Overall, there were 1,066,783 singleton births (175,297 and 891,486 born to non-Hispanic black and non-Hispanic white mothers, respectively). Overall the prevalence of PTB, VPTB, and SGA were 10.9%, 1.2% and 2.2%, respectively, with a higher prevalence evinced for non-Hispanic black mothers in comparison with non-Hispanic white mothers for all birth outcomes examined. We calculated ICC for each outcome. We found that the ICCs were 12%, 10%, and 12% for PTB, VPTB, and SGA respectively. The average number of births by zip code for the study period was 2,074. In general, non-Hispanic black mothers tended to have lower individual socioeconomic status, reside in lower socioeconomic-status neighborhoods, and higher mean exposure to $PM_{2.5}$ than non-Hispanic white mothers (Table 1).

Table 1. Study population characteristics of all singleton live births in California from 2005–2010, by maternal non-Hispanic black or white status [n(%)].

Characteristic	Non-Hispanic black	Non-Hispanic white
Birth outcomes		
Preterm birth		
No	110 247 (87.5)	577354 (89.8)
Yes	20 423 (12.5)	65589 (10.2)
Very preterm birth		
No	148585 (97.4)	772079 (98.9)
Yes	3914 (2.5)	8434 (1.1)
Small for gestational age		
No	143275 (81.7)	803412 (90.1)
Yes	32022 (18.3)	88074 (9.9)
Maternal socioeconomic predictors		
Educational attainment		
<High school	32429 (18.6)	63456 (7.1)
High school or equivalent	58403 (33.4)	192517 (21.7)
Some college	83838 (48.0)	633044 (71.2)
Age at delivery (years)		
<18	7281 (4.2)	9281 (1.0)
18–25	77034 (44.0)	223188 (25.0)
26–34	61794 (35.3)	402725 (45.2)
>34	29153 (16.6)	256251 (28.8)
Medicaid enrollee		
No	81521 (46.5)	696452 (78.1)
Yes	93776 (53.5)	195034 (21.9)
Missing paternal information		
No	139825 (79.8)	847239 (95.0)
Yes	35472 (20.2)	44247 (5.0)
Neighborhood socioeconomic environment predictors		
Unemployment rate		
Q1	31891 (18.4)	421772 (48.8)
Q2	50995 (29.5)	244659 (28.3)
Q3	90055 (52.1)	197968 (22.9)
Poverty rate		
Q1	35895 (20.8)	465311 (53.8)
Q2	59943 (34.7)	274842 (31.8)
Q3	77112 (44.6)	124553 (14.4)
Linguistic minority		
Q1	52965 (30.1)	525444 (60.8)
Q2	67027 (38.8)	248262 (28.7)
Q3	52943 (30.6)	90089 (10.4)
Educational attainment		
Q1	37664 (21.8)	516421 (59.7)
Q2	73687 (42.6)	264304 (30.6)
Q3	61592 (35.6)	83796 (9.7)
Neighborhood air pollution predictors		
NO_2 concentration		
Q1	37721 (21.8)	402835 (46.6)
Q2	59081 (34.2)	276425 (32.0)
Q3	76150 (44.0)	185473 (21.5)
$PM_{2.5}$ concentration		
Q1	53276 (30.8)	396350 (45.9)
Q2	48576 (28.1)	285037 (33.0)
Q3	70907 (41.1)	178367 (20.7)

Descriptive statistics of both the air pollution and neighborhood factors are presented in Supplemental Material (Table S1). Pearson's correlation coefficients between measures of neighborhood socioeconomic environment are presented in Table S2.

Characterizing Black–White Disparities

As supported by previous studies (Braveman et al. 2015; Lu et al. 2010; McKinnon et al. 2016), non-Hispanic black mothers were more likely to deliver early than did non-Hispanic white mother, and they were more likely to have smaller babies than non-Hispanic white mothers did (Table 2). Table 2 presents

Table 2. Crude and adjusted associations between non-Hispanic black status and risk of adverse birth outcome relative to non-Hispanic white (California 2005–2010).

	Crude				Adjusted*			
Category	RR	95% CI	RD	95% CI	RR	95% CI	RD	95% CI
PTB	1.43	1.41, 1.45	0.056	0.054, 0.058	1.39	1.37, 1.41	0.051	0.049, 0.053
VPTB	2.38	2.29, 2.47	0.015	0.014, 0.016	2.29	2.20, 2.39	0.014	0.013, 0.015
SGA	1.85	1.83, 1.87	0.084	0.082, 0.086	1.73	1.70, 1.75	0.073	0.071, 0.075

Note: CI, confidence interval; PTB, preterm birth; RD, risk difference; RR, risk ratio; SGA, small for gestational age; VPTB, very preterm birth.
*Adjusted for infant sex as well as maternal age (continuous), education (<High School, HS graduate or equivalent diploma, any college) Medicare enrollee status, and missing paternal information. Age was also included as a categorical variable as follows: <20, 20–24, 25–29, 30–34, 35 + (25–29 as reference group), but the results were not altered.

crude and adjusted risk ratios and risk differences for PTB, VPTB, and SGA between non-Hispanic black and white mothers. For example, the adjusted effect of racial/ethnic status on preterm birth was a RD of 0.051 (95% CI: 0.049, 0.053), equivalent to a risk increase of 51 additional preterm deliveries per thousand live births.

Tables S3, S4, and S5 present the adjusted risk ratios and adjusted risk differences representing associations between PTB, VPTB, and SGA, respectively, with all the individual, neighborhood, and air pollution variables. The higher estimates (both for RRs and RDs) were for the individual-level estimates. For air pollution exposures, we found that an increase in $PM_{2.5}$ and NO_2 levels were positively associated with the probability of PTB, VPTB, and SGA. In general, we observed effect measures further from the null for individual factors in comparison with neighborhood social factors and air pollution exposure.

Decomposing Black–White Disparities

The predicted black–white difference in probability of outcome was 0.056 (95% CI: 0.054, 0.058), 0.015 (95% CI: 0.014, 0.016), and 0.084 (95% CI: 0.081, 0.087) for PTB, VPTB, and SGA, respectively (Table 3). All included predictors explained the 39.3%, 31.1%, and 30.8% of black–white differences in PTB, VPTB, and SGA, respectively. Almost all variables considered in the study contributed positively to the modeled black–white gap.

Overall, individual- and neighborhood-level variables explained a greater proportion of the black–white differences in birth outcomes than did air pollution. Nonetheless, the individual contribution of $PM_{2.5}$ was comparable in magnitude to any single individual- or neighborhood-level factor. For SGA, $PM_{2.5}$ explained 4.5% (95% CI: 1.0%; 6.8%) of the black–white difference, in comparison with 3.8% (95% CI: 3.0%; 4.5%) and 5.2% (95% CI: 4.7%; 5.7%) for neighborhood poverty and individual Medicaid enrollment, respectively. When considering a composite index of neighborhood socioeconomic environment instead of four distinct variables, the results were similar (see Table S6). We note that, when using this composite index, the overall contribution of the neighborhood socioeconomic environment was slightly reduced for all birth outcomes. This circumstance highlights some possible overlap between the different neighborhood socioeconomic environment factors.

Discussion

Summary of Findings and Comparison to Existing Research

We analyzed births in California to identify the relative contributions of maternal variables, the social environment, and the physical environment to black–white disparities in PTB. Our decomposition approach, which is well-suited to examining disparities but remains rarely used in public health research (Lhila and Long 2012), finds that our included predictors explain approximately 38% of the PTB disparity. Black–white differences in maternal and neighborhood socioeconomic predictors account for roughly the same amount of the disparity (17.5% and 16.1%, respectively). Our results suggest that, in addition to existing disparities-reduction efforts, policies that reduce air pollution may not only improve overall health, but also reduce black–white PTB disparities. Yet, the role of individual and neighborhood factors remains prevailing.

Few studies decompose black–white disparities in PTB (Schempf et al. 2011; Auger et al. 2013), and only one employs the Blinder–Oaxaca decomposition approach (Lhila and Long 2012): thus, it is difficult to compare our main findings. We note that alternative methods to estimate nonlinear decomposition

Table 3. Predicted probability and disparity in PTB, VPTB, and SGA between non-Hispanic black and non-Hispanic white mothers, and percentage of the difference explained by individual, neighborhood socioeconomic, and neighborhood air pollution variables (California 2005–2010).

Race/ethnicity or explanatory variable	PTB estimate (95% CI)	VPTB estimate (95% CI)	SGA estimate (95% CI)
Predicted probability			
Non-Hispanic black mother	0.157 (0.153, 0.159)	0.026 (0.025, 0.027)	0.183 (0.180, 0.185)
Non-Hispanic white mother	0.101 (0.101, 0.102)	0.011 (0.010, 0.011)	0.099 (0.098, 0.100)
Black-white disparity	0.056 (0.054, 0.058)	0.015 (0.014, 0.016)	0.084 (0.081, 0.087)
Percent difference explained			
Total difference explained	39.3%	31.1%	30.8%
Maternal socioeconomic predictors	17.5%	10.5%	30.8%
Educational attainment	4.8 (3.7, 5.7)	4.0 (2.7, 5.6)	4.0 (3.6, 4.4)
Age at delivery	4.6 (3.4, 5.9)	0.3 (−1.1, 2.0)	3.1 (2.7, 3.5)
Medicaid enrollee	5.4 (4.0, 6.7)	1.7 (0.4, 2.9)	5.2 (4.7, 5.7)
Missing paternal information	2.7 (2.1, 3.3)	4.4 (3.2, 5.8)	2.0 (1.7, 2.3)
Neighborhood socioeconomic environment predictors	16.1%	13.2%	12.1%
Unemployment rate	3.8 (2.2, 5.3)	3.4 (1.5, 5.0)	3.2 (2.5, 3.9)
Poverty rate	4.8 (3.1, 6.4)	3.9 (1.9, 5.6)	3.8 (3.0, 4.5)
Linguistic minority	1.9 (0.3, 3.4)	2.0 (0.3, 3.5)	1.4 (0.7, 2.1)
Educational attainment	5.5 (4.5, 6.4)	3.9 (1.9, 5.7)	3.7 (2.9, 4.5)
Neighborhood air pollution predictors	5.7%	7.4%	4.3%
NO_2 concentration	2.6 (−2.1, 5.1)	2.9 (−1.3, 3.9)	0.3 (−0.4, 1.2)
$PM_{2.5}$ concentration	3.1 (0.9, 5.2)	4.5 (0.7, 7.8)	4.0 (1.0, 6.8)

quantities have been developed. For example, Yun (2004) or Fairlie (2005) proposed an application of the Blinder–Oaxaca decomposition to nonlinear models. These papers provide additional discussion of the assumptions and limitations of their respective methods. Notably, attributable disparities may be underestimated if mediators are included in models. Lhila and Long (2012) examined only metropolitan regions, used large regional areas (rather than zip code) as the geographic unit of analysis, and did not assess air pollution. To our knowledge, our analysis is the first to include quantitative air pollution measures. Schempf and colleagues also examined PTB disparities using a fixed-effects approach. They found that a global neighborhood deprivation index accounted for $\sim 15\%$ of the estimated black–white disparity of PTB (Schempf et al. 2011). This finding appears similar in magnitude to the proportion explained by all neighborhood socioeconomic predictors in our approach. However, they found that maternal characteristics (age, education, marital status, and gravidity) accounted for about 40% of the PTB disparity, which is much larger than our decomposition estimates. Differences in study population demographics (i.e., two counties in North Carolina vs. all of California), estimation method, and variables included limit any substantive interpretation of this difference. Decomposition techniques, such as the Blinder–Oaxaca decomposition, partition the gap in an outcome of interest between two groups (here racial/ethnic groups) into an "explained" and an "unexplained" portion, while including simultaneously different contributor factors. Such an approach is particularly superior to classic approaches (such as a pooled regression with a group indicator variable) when many correlated social and environmental factors are assessed simultaneously (Elder et al. 2010). In addition, some studies analyzed the contribution of different factors in a given relationship by including all measured predictors in a standard regression model and then estimated the percentage change in the original estimate of interest by removing sequentially each factor. For example, Dadvand et al. (2014) evaluated the roles of air pollution, heat, noise, and green space in explaining the observed association between proximity to major roads and low birth weight in Spain. Although such an approach can be informative when investigating the role that a specific factor plays in the difference between two groups, it does not provide information on the explained and unexplained components of the outcome and does not allow for the assessment of several factors simultaneously.

Interpretation

There are two main differences between past findings and ours. First, we find a greater proportional influence of neighborhood predictors for black–white PTB disparities than in earlier work. This difference may arise from our use of poverty levels and linguistic isolation, which may better gauge area of deprivation and, by extension, the social stressors that may contribute to disparities in PTB (Schempf et al. 2011). Second, and relatedly, we separately identified the contribution of neighborhood air pollution to disparities, an increasingly important predictor of adverse birth outcomes (Burris et al. 2011; Arroyo et al. 2016; Stieb et al. 2012). Importantly, we found differences in mean annual $PM_{2.5}$ to explain nearly as much of the PTB disparity as recognized strong predictors of PTB, such as maternal age and education (Blumenshine et al. 2010). Moreover, it is surprising that such a strong relationship was observed despite likely substantial misclassifications of air pollution exposure actually experienced by pregnant mothers during etiologically relevant periods. These findings cohere with environmental justice literature related to air pollution exposures (Woodruff et al. 2003; Gwynn and Thurston 2001; O'Neill et al. 2003).

A substantial proportion of the black–white disparity remains unexplained by our study's included factors. For example, some other modifiable factors have not been included in the study, such as cigarette smoking and/or exposure to lead or pesticides. In addition, residual confounding can be present. For example, it is possible that women living in high poverty areas may smoke more than women living in low poverty areas, and such aspect was not considered in our models. We do not believe that the residual unexplained disparity arises from group factors such as genetic ancestry (Butler and Behrman 2007). However, we would caution against such an over-interpretation of the unexplained variation. For instance, in their decomposition analysis in Brazil where a spectrum of genetic admixtures could be studied, Nyarko, et al. (2014) found individual, household, medical, and geographic factors could explain up to 94% of the disparity. Moreover, the decomposition analysis approach highlights the fact that unexplained variation can be due to factors such as variable parameterization and not only unmeasured confounding. In the decomposition procedure that was used in this study, we did not capture possible effect modification between factors that have been investigated and status of race/ethnicity. We, rather, focused on differences in exposures. Indeed, future work could consider an additive effect modification between status of race/ethnicity and each of the predictors considered in this study. For example, the environmental justice literature reports that at least two distinct types of disparities exist (Forastiere et al. 2007, Cartier et al. 2015, Hajat et al. 2015): differential exposure (which was considered in the present study) and differential susceptibility or effect modification (which was not captured in the decomposition procedure). Such effect modification by race/ethnicity could also contribute to the residual unexplained disparity.

Study Limitations and Recommendations for Further Studies

Other major causes of PTB, including differences in individual maternal biochemical factors such as the vaginal microbiome or infections, may explain some of the disparity (Lu et al. 2010; Butler and Behrman 2007). Moreover, black women may be more susceptible to inflammatory sequelae of infection due to social or biological stressors. This susceptibility may both account for some of the residual variance in disparities and partially explain some of the variance due to measured socioeconomic characteristics. We also cannot rule out the possibility that some area-level factors (e.g., poverty rate) may precede increases in air pollutants. Another limitation is related to the use of the zip code–level data as a measure of neighborhood social environment. Using such a scale may not represent the local socioeconomic status (SES) environment—especially in rural areas with large zip code regions—and therefore, could lead to neighborhood SES exposure misclassification. Additionally, possible sensitivity analysis could be conducted in the future with further data like using the air pollution exposure only during the pregnancy period. However, we considered annual exposures, which approximate the full pregnancy exposure and has been found to be the most relevant in prior studies of air pollution and PTB (Green et al. 2015, Zhu et al. 2015). The exposure was assigned at the zip code level, which may reduce spatial variability in comparison with individual-level air pollution exposures. In addition, systematic measurements errors in air pollution levels by racial/ethnic group are possible if the monitors are not randomly spatially distributed. Another issue relates to the lack of direct comparability of units across the different measures. To facilitate the comparison of the strength of the coefficients, we used tertiles in both neighborhood and air pollution factors.

Another limitation of our study is that we investigated only exposure to $PM_{2.5}$ and NO_2 in this study. $PM_{2.5}$ and NO_2 are widely studied air pollutants for pregnancy outcomes (Green et al. 2015, Zhu et al. 2015). NO_2 captures the spatial variation in outdoor, urban, air pollutant mixtures (Levy et al. 2014), and $PM_{2.5}$ can harm human health due to its small diameter, large surface area, and toxic chemical species that PM carries. Other co-pollutants or environmental exposures resulting from similar sources (e.g., ultrafine particles and noise) can enhance the contribution of $PM_{2.5}$ and NO_2

Implications for Public Health

It is well recognized that individualized, clinical perinatal interventions have not been successful in reducing either the absolute risk of PTB or other adverse birth outcomes among U.S. black women, nor in reducing disparities relative to U.S. white women (Blumenshine et al. 2010; Butler et al. 2007). Recently, the importance of the contribution of differences in neighborhood environment and exposure to air pollution to black–white disparities in adverse birth outcomes has received increasing attention. Our findings suggest that such a focus is warranted, because we find that measured factors such as average $PM_{2.5}$ exposure is also a contributor to racial/ethnic disparities. Reducing $PM_{2.5}$ exposure through diverse equitable air pollution policies (Benmarhnia et al. 2014) in high-exposure zip codes may help reduce black–white disparities in PTB.

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