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Abstract

Maternal preconception health and neighborhood factors in relation to preterm birth in Georgia,
2012-2014

By

Michelle Sarah Livings

November 27, 2017

Abstract:

BACKGROUND: Relationships between maternal preconception health and preterm birth have been demonstrated in the literature, as have relationships between neighborhood factors and maternal preconception health. Determining how maternal preconception health and neighborhood factors simultaneously contribute to preterm birth will help researchers and clinicians better understand the complex risk factors of preterm birth.

METHODS: Data were collected during 2012-2014 in the Georgia Pregnancy Risk Assessment Monitoring System. Data were geocoded to American Community Survey 2011-2015 5-year estimates ($n=3085$). Descriptive statistics were calculated. Effects of maternal preconception health and neighborhood factors on preterm birth were analyzed using hierarchical generalized linear modeling (SAS PROC GLIMMIX).

RESULTS: From 2012-2014, about 9.38% of Georgia moms gave birth to a preterm infant. Considering cross-level interactions, for women who reported recently dieting and lived in census tracts with 1.00% more crowded households than average, the estimated odds of preterm birth were 0.83 times the estimated odds for the average interaction (95% CI 0.81-0.85). For women with a pre-pregnancy chronic disease who lived in rural counties, the estimated odds of preterm birth were 1.35 times the estimated odds for the average interaction (95% CI 1.17-1.57).

CONCLUSIONS: Maternal preconception health and neighborhood factors were simultaneously significantly associated with preterm birth, demonstrating the complexity of risk factors associated with preterm birth. Programs to promote healthy weight management and exercise before pregnancy and to encourage physicians to work in rural counties could improve maternal preconception health and decrease preterm births.

**Maternal preconception health and neighborhood factors in relation to preterm birth in
Georgia, 2012-2014**

by

Michelle Sarah Livings

B.S., Stevens Institute of Technology

A Thesis Submitted to the Graduate Faculty
of Georgia State University in Partial Fulfillment
of the
Requirements for the Degree

MASTER OF PUBLIC HEALTH

ATLANTA, GEORGIA
30303

APPROVAL PAGE

Maternal preconception health and neighborhood factors in relation to preterm birth in Georgia,

2012-2014

by

Michelle Sarah Livings

Approved by:

Dr. Betty Lai
Committee Chair

Dr. Ann-Margaret Esnard
Committee Member

Florence Kanu
Committee Member

Date: November 27, 2017

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I am dedicating this thesis to my grandmother. I love you.

Author's Statement Page

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Michelle Sarah Livings

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Introduction

Preterm birth is one of the leading causes of infant mortality in the United States (CDC, 2016). Babies who are born preterm (i.e., more than three weeks before their due date) have a higher risk of death or serious disability, such as breathing, vision, and hearing problems, as well as learning disabilities (CDC, 2017a; WHO, 2016). Preterm birth is an issue of particular concern in Georgia, where in 2015, the incidence of preterm birth (10.8%) was higher than the national average (9.6%; NCHS, 2017a; NCHS, 2017b). Research using state-level data from Georgia would not only clarify the best options for decreasing the rate of preterm birth in Georgia, but would also help researchers and clinicians understand preterm birth risk factors in states with similar sociodemographics.

Improving maternal and child health requires investigating whether and how maternal preconception health indicators and neighborhood factors simultaneously contribute to preterm birth. A 2007 report about the causes, consequences, and prevention of preterm birth published by the Institute of Medicine stated that preterm birth is “a complex cluster of problems with a set of overlapping factors of influence.” The report listed numerous factors as influencing preterm birth, including individual-level behavioral factors, psychosocial factors, and medical conditions; environmental exposure; genetics; and neighborhood characteristics; and further stated that multiple factors often collectively contribute to preterm birth (Institute of Medicine, 2007). The effects of both individual-level factors and neighborhood-level characteristics on an outcome can be examined simultaneously using multilevel modeling.

There is a dearth of literature examining how neighborhood factors and maternal preconception health (i.e., the health of a reproductive-aged woman before she becomes pregnant) simultaneously affect preterm birth. Previous research has examined how neighborhood factors and *other* maternal-level factors relate to adverse birth outcomes; *other*

maternal-level factors included pregnancy intention, breastfeeding, and prenatal care (Cubbin et al., 2008); maternal smoking (Nkansah-Amankra, 2010; Vinikoor-Imler, Messer, Evenson, & Laraia, 2011); maternal social support (Nkansah-Amankra, Dhawain, Hussey, & Luchok, 2010); maternal stress (Nkansah-Amankra, Luchok, Hussey, Watkins, & Liu, 2010); and inadequate or excessive weight gain during pregnancy (Vinikoor-Imler et al., 2011). While such studies have provided substantial contributions to the field, examining maternal preconception health indicators together with neighborhood factors is essential in order to decrease preterm birth rates and improve maternal and child health.

Investigating how both maternal preconception health indicators and neighborhood factors contribute to preterm birth is essential to fully understand the risk factors for preterm birth at various levels and to better inform policies and programs related to maternal and child health. Maternal preconception health influences the health of both a woman and her baby during pregnancy. Relationships between maternal preconception health indicators and preterm birth have been well documented in the literature (Alder, Fink, Bitzer, Hosli, & Holzgrene, 2007; Frayne et al., 2016; Vernini et al., 2016). Additionally, as of 2011, approximately 45% of pregnancies in the U.S. were unintended (Finer & Zolna, 2016). Maternal preconception health is therefore an important factor to consider in order to promote healthy pregnancies and healthy babies (Nypaver, Arbour, & Niederegger, 2016). Further, studies have shown that the neighborhood where a woman lives before and during pregnancy has an impact on her health before conception and during pregnancy, as well as impacting the health of her baby (Mendez, Hogan, & Culhane, 2014; O'Campo, Xue, Wang, & Caughy, 1997; Wallace et al., 2013).

The goal of this study was to examine how maternal preconception health indicators and neighborhood factors simultaneously contribute to preterm birth in Georgia. *Maternal*

preconception health indicators included maternal body mass index (BMI) before pregnancy; diet and exercise behaviors before pregnancy; and presence of pre-pregnancy chronic disease, specifically hypertension, diabetes, and/or depression. *Neighborhood factors* included proportion of households in a census tract with income below the federal poverty line; proportion of census tract residents with less than a high school education; household crowding; and urban-rural status.

Methods

Data sources. The Pregnancy Risk Assessment Monitoring System (PRAMS) is a research project of the Centers for Disease Control and Prevention (CDC) and state health departments designed to collect state-specific data about maternal experiences and behaviors before, during, and shortly after pregnancy, supplementing information provided on birth certificates (CDC, 2017b). As of 2016, 47 states participate in PRAMS, as well as New York City (separate from New York PRAMS), Washington, D.C., Puerto Rico, and the Great Plains Tribal Chairmen's Health Board.

Georgia has collected PRAMS data since 1993. Each month, approximately 100-200 women are selected from recent birth certificates using stratified random sampling (Georgia Department of Public Health, 2017). Women are eligible to participate in Georgia PRAMS if they are a Georgia resident and if they have given birth to a live baby within the past two to six months. Surveys are mailed to each woman selected to participate in Georgia PRAMS. The Georgia PRAMS survey consists of approximately 80 self-report questions about a variety of topics relating to a mother's attitudes, knowledge, and behaviors before, during, and shortly after pregnancy. Topics include maternal preconception health behaviors, maternal stress, pregnancy intention, contraceptive use, prenatal care, tobacco and alcohol use, pregnancy-related morbidity,

vaccinations, HIV testing, postpartum depressive symptoms, infant safe sleep, breastfeeding, and maternal knowledge of pregnancy-related health issues. If surveys are not returned by mail, attempts are made to conduct the survey over the phone. At the end of each data collection year, each state submits their PRAMS data to the CDC, where the data are weighted. The CDC requires a minimum overall response rate of 60% for data collected after 2011. Georgia PRAMS data are also linked to birth certificate data, including infant birth weight, gestational age at birth, and maternal and paternal demographic information.

This study was approved by the Institutional Review Boards at Georgia State University and the Georgia Department of Public Health. Georgia PRAMS data from PRAMS Phase 7 (data years 2012-2014) were examined in this study; these were the most current data available at the time of analysis. Women who participated in Georgia PRAMS during this time frame each received a \$10 Walmart gift card as a reward for their participation. Georgia PRAMS data from 2012 and 2013 were above the 60% response rate threshold (overall unweighted response rates of 65.27% and 65.89%, respectively). Georgia PRAMS data from 2014 did not meet the 60% response rate threshold (overall unweighted response rate of 50.24%); however, data were still weighted by the CDC to be as generalizable to the population of Georgia as possible.

This study analyzed geocoded Georgia PRAMS data from 2012-2014 together with data from the American Community Survey (ACS) 2011-2015 5-year estimates using the census tract as the common linking variable. Georgia PRAMS data were geocoded by converting mothers' street addresses to latitude and longitude coordinates and then matching the coordinates to Georgia 2010 census tracts using GIS software. The geocoded PRAMS database included the GeoID of each participant's census tract, along with PRAMS data and birth certificate data; no identifying information were provided. The geocoded PRAMS database was merged with

selected variables from the ACS 2011-2015 5-year estimates to create a multilevel dataset, including maternal factors as the first level and neighborhood factors as the second level.

Neighborhoods were defined as census tracts in this study, based on previous literature (Cubbin et al., 2008; Nkansah-Amankra, 2010; O'Campo et al., 1997).

Study population. Geocoding of 2012-2014 Georgia PRAMS data to 2010 census tracts achieved a completeness of 96.80%; 5,179 out of 5,350 total PRAMS mothers were successfully linked to 1,485 census tracts in Georgia. Mothers with addresses outside of Georgia ($n=8$) were excluded from this study, as were mothers whose addresses were not successfully geocoded ($n=163$). The study sample was further condensed by excluding those women who were selected but did not participate in the Georgia PRAMS survey ($n=2,094$). Overall, 42.34% of the original sample was excluded, resulting in a study sample of 3,085 women who gave birth to a live infant in 2012, 2013, or 2014.

PRAMS sites may choose to oversample from specific populations, to ensure that those populations are well represented in the study data and to allow for meaningful analysis regarding generally underrepresented populations and disparities. In 2012, Georgia PRAMS oversampled teen mothers and mothers of low birth weight babies (maternal age < 20 years, birth weight < 2,500 grams), and in 2013 and 2014, Georgia PRAMS oversampled mothers residing in specific counties identified as infant mortality clusters in 2012 (Bibb, Chatham, Fulton, Lowndes, Muscogee, and Richmond counties; Georgia Department of Public Health, 2017).

Birth outcome. Gestational age was available from the birth certificate and was used to define the outcome of interest. *Preterm birth* was defined as gestational age less than 37 weeks at time of birth (WHO, 2016). *Preterm birth* was analyzed as a dichotomous variable (1=preterm, < 37 weeks' gestation; 0=full-term, ≥ 37 weeks' gestation).

Maternal-level variables. Indicators from 2012-2014 Georgia PRAMS were used to represent maternal preconception health. Effect coding was used instead of dummy coding for dichotomous predictors in order to minimize multicollinearity between dichotomous predictors and interaction terms.

Maternal BMI before pregnancy was a continuous variable, and was group-mean centered per the recommendations by Enders and Tofghi (2007) pertaining to level-1 predictors.

Recently dieting was defined using the survey question: “At any time during the 12 months before you got pregnant with your new baby, were you dieting (changing your eating habits) to lose weight?” *Recently dieting* was a dichotomous variable (1=Yes; -1=No), and was uncentered.

Regular exercise was defined using the survey question: “At any time during the 12 months before you got pregnant with your new baby, were you exercising 3 or more days of the week?” *Regular exercise* was a dichotomous variable (1=Yes; -1=No), and was uncentered.

Presence of pre-pregnancy chronic disease was defined using the survey question: “Before you got pregnant with your new baby, did a doctor, nurse, or other health care worker tell you that you had any of the following health conditions: Type 1 or Type 2 diabetes (NOT the same as gestational diabetes or diabetes that starts during pregnancy); High blood pressure or hypertension; or Depression?” *Presence of pre-pregnancy chronic disease* was a dichotomous variable (1=Yes=a positive response to one or more of the three options; -1=No=negative responses to all three options), and was uncentered.

Maternal covariates. Several maternal-level variables were considered as potential confounders: maternal age (continuous, group-mean centered), race/ethnicity (uncentered; effect coded with non-Hispanic black, Hispanic, and non-Hispanic other as measured effects, and non-

Hispanic white as the reference group), education (uncentered; effect coded with “less than high school” and “more than high school” as measured effects, and “high school graduate” as the reference group), marital status (1=married; -1=not married; uncentered), and payment for delivery (1=Medicaid; -1=other; uncentered). Payment for delivery was used as a proxy for income, as the self-reported income variable was over 30% missing in the PRAMS dataset.

Neighborhood-level variables. Neighborhood factors were obtained from the 2011-2015 ACS 5-year estimates for all Georgia census tracts. Three variables were selected as measures of social determinants of health disparities, based on previous studies (Datta et al., 2006; Huynh, Parker, Harper, & Schoendorf, 2005; Nkansah-Amankra, 2010); a fourth variable, *urban-rural status*, was included to further describe the neighborhood environment.

Neighborhood poverty – the proportion of households in a census tract with income below the federal poverty line – was a continuous variable, and was grand-mean centered per the recommendations by Enders and Tofighi (2007) pertaining to level-2 predictors.

Low education – the proportion of residents in a census tract with less than a high school education – was a continuous variable, and was grand-mean centered per the recommendations by Enders and Tofighi (2007) pertaining to level-2 predictors.

Household crowding – proportion of households in a census tract with more than one person per room – was a continuous variable, and was grand-mean centered per the recommendations by Enders and Tofighi (2007) pertaining to level-2 predictors.

Urban-rural status was defined by Georgia PRAMS. Counties with less than 35,000 people were considered “rural,” while counties with more than 35,000 people were considered “urban.” *Urban-rural status* was analyzed as a dichotomous variable (1=rural; -1=urban), and was uncentered.

Results

Analyses were performed using SAS version 9.4 (SAS Institute Inc., Cary, NC) and SAS-callable SUDAAN version 11.0.1 (RTI International, Research Triangle Park, NC). All analyses incorporated a weighting variable, provided by CDC, to account for sample selection, oversampling, and non-response, and to more accurately reflect the population of women delivering live babies in Georgia from 2012 to 2014.

First, descriptive statistics were calculated using SUDAAN PROC CROSSTAB. Weighted participant demographics and maternal preconception health indicators, stratified by birth outcome (i.e., preterm birth, full-term birth), are displayed in Table 1. From 2012-2014, approximately 9.38% of women in Georgia ($n=484$; weighted $n=28,531$) gave birth to a preterm infant. Neighborhood characteristics, stratified by birth outcome, are displayed in Table 2. For descriptive statistics, neighborhood poverty was separated into tertiles, while low education and household crowding were separated into quartiles, based on similar analytic procedures performed by Datta et al. (2006) and Nkansah-Amankra (2010).

Then, to address the main study aim regarding how maternal preconception health indicators and neighborhood factors interact with the outcome *preterm birth* in Georgia, hierarchical generalized linear models were analyzed. SAS PROC GLIMMIX was used to fit a two-level hierarchical generalized linear model for the dichotomous outcome *preterm birth*, assuming a binomial distribution and a logit link function, and using the census tract GeoID as the clustering variable. Variance components were estimated using maximum pseudo-likelihood; the expansion locus was the vector of random effects solutions. A model was built to examine the relationships between preterm birth, maternal preconception health indicators, maternal covariates, neighborhood factors, and cross-level interaction terms.

An unconditional hierarchical generalized linear model was analyzed first, with no predictors and a random effect for the intercept. The interclass correlation coefficient was calculated to be 0.85. Approximately 85% of the variability in birth outcome was accounted for by neighborhood factors, leaving about 15% of the variability in birth outcome to be accounted for by individual maternal indicators or other unknown factors. Further, there was a statistically significant amount of variability in the log odds of birth outcome between census tracts in the unconditional model [$\tau_{00} = 18.36$, $Z = 20.69$, $p < 0.0001$], indicating that rates of preterm birth varied across neighborhoods.

Next, fixed effects were added into the model for each maternal preconception health indicator, each maternal covariate, and each neighborhood factor, in addition to a random effect for the intercept. Fixed effects for cross-level interaction terms were added to the model using a sequential fitting procedure, as described in Urquia et al. (2009). Prior to calculating cross-level interaction terms, level-1 predictors were group-mean centered and level-2 predictors were grand-mean centered (including dichotomous predictors). The final model included a random effect for the intercept, plus fixed effects for all maternal preconception health indicators, all maternal covariates, all neighborhood factors, and nine cross-level interaction terms (*maternal BMI* \times *neighborhood poverty*, *maternal BMI* \times *low education*, *maternal BMI* \times *household crowding*, *recently dieting* \times *neighborhood poverty*, *recently dieting* \times *low education*, *recently dieting* \times *household crowding*, *regular exercise* \times *neighborhood poverty*, *regular exercise* \times *low education*, and *presence of pre-pregnancy chronic disease* \times *urban-rural status*). All assumptions for a two-level hierarchical generalized linear model were met.

Coefficient estimates and odds ratio estimates with corresponding 95% confidence intervals for all predictors and interaction terms are displayed in Table 3. Odds ratio estimates

were significantly different than 1.00 for maternal BMI before pregnancy, recently dieting, presence of chronic disease, urban-rural status, and all nine cross-level interaction terms.

The estimated odds of preterm birth among women who reported that they were recently dieting were 0.73 times the estimated odds of preterm birth among women who were not recently dieting (95% CI 0.69-0.77), controlling for all other predictors. The estimated odds of preterm birth among women who reported at least one pre-pregnancy chronic disease were 0.57 times the estimated odds of preterm birth among women who had no chronic diseases before pregnancy (95% CI 0.52-0.63), controlling for all other predictors. The estimated odds of preterm birth in rural counties were 3.08 times the estimated odds of preterm birth in urban counties (95% CI 2.33-4.07), controlling for all other predictors. Considering cross-level interactions, for women who reported recently dieting and lived in census tracts with 1% more crowded households than average, the estimated odds of preterm birth were 0.83 times the estimated odds for the average interaction (95% CI 0.81-0.85), controlling for all other predictors. For women with a pre-pregnancy chronic disease who lived in rural counties, the estimated odds of preterm birth were 1.35 times the estimated odds for the average interaction (95% CI 1.17-1.57), controlling for all other predictors. While the estimated odds ratios for the other interaction terms were statistically significant, they ranged from 0.97 to 1.05, and were thus not substantially different from 1.00.

Discussion

This study was the first step to understanding how maternal preconception health indicators and neighborhood factors simultaneously contribute to preterm birth. Three of the four maternal preconception health indicators, one of the four neighborhood factors, and all nine cross-level interaction terms that were analyzed in this study significantly influenced preterm birth. By examining odds ratios for the predictors and interaction terms, we reached the

conclusion that maternal-level and neighborhood-level factors simultaneously contribute to birth outcome.

Several results were especially striking. Results pertaining to maternal preconception health indicators reiterate the importance of reaching and maintaining a healthy weight and exercising before getting pregnant. Surprisingly, the odds of preterm birth for women with a pre-pregnancy chronic disease were substantially lower than the odds for women with no chronic diseases, even controlling for maternal covariates. Women with a pre-pregnancy chronic disease may visit their doctor or health care professional more often than women with no chronic diseases, for disease maintenance purposes. This regular health care before pregnancy would likely lead to particularly careful monitoring during pregnancy, which may contribute to the decreased odds of preterm birth among women with a pre-pregnancy chronic disease; a similar conclusion was reached by Orr et al. (2012). Additionally, only one of the examined neighborhood factors, urban-rural status, was significantly associated with preterm birth. The odds of preterm birth for women in rural counties were substantially higher than the odds for women in urban counties, as previously shown in Kent et al. (2013). This may be due to limited health care access in rural counties, but numerous other factors could contribute to this increased odds, such as access to healthy food or environmental hazards at the neighborhood level, or employment status at the individual level.

To our knowledge, this is the first study to examine how maternal preconception health indicators and neighborhood factors concurrently influence preterm birth. Further, the results of this study substantially add to the literature by showing that maternal preconception health indicators and neighborhood factors were simultaneously significantly associated with preterm birth, demonstrating the complexity of the risk factors associated with preterm birth. Two cross-

level interactions had estimated odds ratios substantially different from 1.00. The odds of preterm birth were lower among women who reported dieting before pregnancy who lived in neighborhoods with higher percentages of household crowding, compared to women with an average interaction between recently dieting and household crowding. Household crowding may be a protective factor in relation to dieting before pregnancy and birth outcome. One possible explanation is that women who live in neighborhoods with higher percentages of household crowding follow healthier diets because of live-in support from family or roommates, resulting in healthier pregnancies and decreased odds of preterm birth. Another possible explanation could be related to low income and limited availability of food in the household, forcing individuals in the household to “diet.” However, no studies have been published to date regarding the relationship between dieting and household crowding.

In contrast, the odds of preterm birth were higher among women with a chronic disease before pregnancy who lived in a rural county, compared to women with an average interaction between pre-pregnancy chronic disease and urban-rural status. This relationship between chronic disease and rural environment has been demonstrated in other studies. For example, the Women-to-Women project is a telehealth program being implemented in isolated, rural areas of five western states (Winters, Cudney, Sullivan, & Thuesen, 2006). Of the topics discussed in Women-to-Women online support groups, rural environment was most often cited as a factor affecting women living with chronic diseases, including distance, travel limitations, physical isolation, and health hazards (Winters et al., 2006). Similar factors likely affect women with chronic diseases who live in rural counties during pregnancy, potentially increasing the odds of preterm birth.

These cross-level interactions demonstrate the importance of programs and policies to address both individual-level and neighborhood-level factors. In particular, health care access and programs to educate individuals about chronic disease maintenance are needed in rural counties. The Georgia Board for Physician Workforce sponsors a Physicians for Rural Areas Assistance Program, which assists rural physicians with medical school loan repayment (2016). In 2017, this program offered awards to 36 rural physicians in Georgia (GBPW, 2016), but there are over 100 rural counties in Georgia. Other states have similar funding opportunities, as does the federal government, but similar to Georgia, there is not enough funding for the number of physicians needed in rural areas. The Institute of Medicine estimated that, in 2007, the U.S. spent approximately \$26.2 billion on costs associated with preterm birth (e.g., labor and delivery costs for moms, medical costs for preterm infants, special education services for children with disabilities resulting from being born preterm; 2007). Additional funding opportunities and loan forgiveness programs for rural physicians could address several preterm birth risk factors, and would be a small investment compared to the costs that could be avoided by reducing the rate of preterm birth.

Limitations. Several limitations should be considered when interpreting results. First, the 2014 Georgia PRAMS data did not meet the 60% threshold response rate; the Georgia Department of Public Health (2017) recommends not comparing 2014 Georgia PRAMS data with data from other PRAMS sites. Second, the study population included only Georgia resident women, and thus results are not directly generalizable to other states, although results may be similar for other southeastern states and/or states with a sociodemographic makeup similar to that of Georgia. Third, maternal preconception health indicators (specifically recently dieting and regular exercise) provided only a limited picture for analysis. Some women may have been on a

several-year diet and/or exercise program, while others may have started dieting and/or exercising shortly before finding out they were pregnant.

Future directions. The results of this study suggest several directions for further analysis. First, because results may not be directly generalizable to other states, this study should be replicated using geocoded data from other PRAMS sites. Second, researchers should perform similar studies with additional neighborhood-level variables (e.g., unemployment, housing conditions, food desert status, crime) to provide more information regarding specific neighborhoods that would draw the most benefit from programs and funding. Finally, a hot spot analysis of preterm births within the state of Georgia or the southeastern U.S. would allow for further investigation into particular regions or counties with large numbers of preterm births.

In conclusion, this study examined how maternal preconception health indicators and neighborhood factors together impact preterm birth. The results of this analysis allowed us to identify neighborhoods with characteristics significantly associated with preterm birth, and to recommend programs to ultimately reduce the rate of preterm births in Georgia. Conducting similar analyses with data from other states could help determine whether it would be beneficial to implement similar programs nationwide. Specifically, programs to promote good nutrition, healthy weight management, and exercise before pregnancy are needed, both to improve women's health before pregnancy, and to decrease the rate of preterm birth. Further, increasing funding opportunities and loan forgiveness programs to encourage more physicians to work in rural counties and to thus increase health care access in rural counties could improve chronic disease maintenance and also decrease the rate of preterm birth.

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Table 1: Maternal Characteristics by Birth Outcome

Characteristic	Preterm Birth, Weighted % (95% CI)	Full-Term Birth, Weighted % (95% CI)
Total	9.38 (7.99, 11.00)	90.62 (89.00, 92.01)
Age		
< 20 years	9.48 (5.17, 16.75)	7.60 (6.46, 8.91)
20 – 29 years	51.26 (42.90, 59.55)	51.38 (48.42, 54.33)
30 + years	39.26 (31.53, 47.57)	41.02 (38.13, 43.98)
Race / Ethnicity		
Non-Hispanic White	44.45 (36.14, 53.08)	47.71 (44.71, 50.73)
Non-Hispanic Black	39.30 (31.53, 47.64)	30.50 (27.82, 33.33)
Hispanic	10.97 (6.72, 17.42)	15.75 (13.68, 18.07)
Non-Hispanic Other	5.28 (2.69, 10.11)	6.04 (4.74, 7.67)
Education		
< High School	17.45 (12.07, 24.57)	15.63 (13.57, 17.95)
High School Graduate	36.51 (28.44, 45.42)	29.98 (27.26, 32.84)
> High School	46.03 (37.83, 54.46)	54.39 (51.37, 57.38)
Marital Status		
Married	47.71 (39.45, 56.10)	57.27 (54.28, 60.20)
Other	52.29 (43.90, 60.55)	42.73 (39.80, 45.72)
Payment for Delivery ^a		
Medicaid	55.51 (46.91, 63.79)	46.95 (43.94, 49.98)
Other	44.49 (36.21, 53.09)	53.05 (50.02, 56.06)
Maternal BMI Before Pregnancy		
Underweight (BMI < 18.5)	17.18 (12.00, 23.98)	14.88 (12.85, 17.16)
Healthy (18.5 ≤ BMI ≤ 24.9)	42.40 (34.21, 51.02)	38.09 (35.24, 41.02)
Overweight (25.0 ≤ BMI ≤ 29.9)	21.12 (15.35, 28.33)	25.11 (22.62, 27.78)
Obese (BMI ≥ 30)	19.31 (13.59, 26.70)	21.93 (19.55, 24.51)
Recently Dieting ^b		
Yes	18.90 (13.29, 26.16)	26.42 (23.88, 29.14)
No	81.10 (73.84, 86.71)	73.58 (70.86, 76.12)
Regular Exercise ^c		
Yes	37.54 (29.94, 45.80)	45.49 (42.53, 48.47)
No	62.46 (54.20, 70.06)	54.51 (51.53, 57.47)
Presence of Pre-Pregnancy Chronic Disease		
Yes	13.93 (8.76, 21.43)	8.42 (6.89, 10.24)
No	86.07 (78.57, 91.24)	91.58 (89.76, 93.11)

Note. CI = confidence interval; BMI = body mass index; ^aPayment for delivery used as a proxy for income;

^bReported dieting or changing eating habits to lose weight in the 12 months before pregnancy; ^cReported exercising 3 or more times per week in the 12 months before pregnancy.

Table 2: Participant Neighborhood Demographics by Birth Outcome

Characteristic	Preterm Birth, Weighted % (95% CI)	Full-Term Birth, Weighted % (95% CI)
Total	9.38 (7.99, 11.00)	90.62 (89.00, 92.01)
Neighborhood Poverty		
< 13.3% Below Poverty Line	36.36 (28.87, 44.58)	37.56 (34.74, 40.46)
13.3 – 26.4% Below Poverty Line	31.61 (24.50, 39.68)	36.27 (33.44, 39.20)
> 26.4% Below Poverty Line	32.04 (24.90, 40.12)	26.17 (23.67, 28.84)
Low Education		
< 20.25% Less than HS Education	20.18 (14.85, 26.82)	23.15 (20.78, 25.71)
20.25 – 31.80% Less than HS Education	22.36 (16.43, 29.68)	25.99 (23.47, 28.68)
31.80 – 47.90% Less than HS Education	25.78 (19.12, 33.79)	23.72 (21.28, 26.36)
> 47.90% Less than HS Education	31.67 (24.31, 40.09)	27.13 (24.55, 29.87)
Household Crowding		
< 0.59% More than 1 Person Per Room	23.18 (17.21, 30.47)	28.00 (25.40, 30.75)
0.59 – 2.03% More than 1 Person Per Room	24.91 (18.79, 32.23)	23.86 (21.43, 26.49)
2.03 – 3.95% More than 1 Person Per Room	21.62 (15.35, 29.57)	22.12 (19.78, 24.65)
> 3.95% More than 1 Person Per Room	30.29 (23.12, 38.57)	26.02 (23.49, 28.72)
Urban-Rural Status		
Urban (> 35,000 People Per County)	71.13 (62.83, 78.22)	73.80 (71.04, 76.39)
Rural (< 35,000 People Per County)	28.87 (21.78, 37.17)	26.20 (23.61, 28.96)

Note. CI = confidence interval.

Table 3: β -Coefficient Estimates and Odds Ratio Estimates for Preterm Birth by Maternal Preconception Health Indicators, Neighborhood Factors, and Cross-Level Interactions

Predictor	β Estimate	Odds Ratio Estimate (95% CI)
Maternal Preconception Health Indicators		
Maternal BMI Before Pregnancy	0.04*	1.04 (1.03, 1.04)
Recently Dieting	-0.31*	0.73 (0.69, 0.77)
Regular Exercise	-0.04	0.96 (0.93, 1.00)
Presence of Chronic Disease	-0.56*	0.57 (0.52, 0.63)
Neighborhood Factors		
Neighborhood Poverty	0.01	1.01 (0.98, 1.04)
Low Education	-0.02	0.98 (0.96, 1.00)
Household Crowding	0.01	1.01 (0.89, 1.15)
Urban-Rural Status	1.12*	3.08 (2.33, 4.07)
Maternal \times Neighborhood Interactions		
BMI \times Neighborhood Poverty	-0.01*	1.00 (1.00, 1.00) ^a
BMI \times Low Education	0.00* ^b	1.00 (1.00, 1.00) ^c
BMI \times Household Crowding	0.01*	1.01 (1.01, 1.02)
Diet \times Neighborhood Poverty	0.02*	1.02 (1.02, 1.02) ^d
Diet \times Low Education	-0.01*	0.99 (0.99, 1.00)
Diet \times Household Crowding	-0.19*	0.83 (0.81, 0.85)
Exercise \times Neighborhood Poverty	0.05*	1.05 (1.04, 1.05)
Exercise \times Low Education	-0.03*	0.97 (0.97, 0.97) ^e
Chronic Disease \times Urban-Rural Status	0.30*	1.35 (1.17, 1.57)

Note. CI = confidence interval; BMI = body mass index; * $p < 0.05$ based on Wald F -test; ^a Expanded to 3 decimal places, this estimate was 0.995 (0.995, 0.996); ^b Expanded to 3 decimal places, this estimate was 0.002; ^c Expanded to 3 decimal places, this estimate was 1.002 (1.002, 1.003); ^d Expanded to 3 decimal places, this estimate was 1.019 (1.015, 1.024); ^e Expanded to 3 decimal places, this estimate was 0.917 (0.969, 0.973).