MATERNAL SOURCES OF STRESS WITHIN HER COMBINED INDIVIDUAL AND NEIGHBORHOOD ENVIRONMENT AND THE RISK OF PREECLAMPSIA

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Ethan Samuel Blum

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This thesis was presented

by

Ethan Samuel Blum

It was defended on

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and approved by

James M Roberts MD**,** Investigator Magee-Womens Research Institute, Professor, Department of Obstetrics, Gynecology & Reproductive Sciences, and Clinical Translational Research, University of Pittsburgh

Dara D Mendez PhD, MPH, Assistant Professor, Department of Epidemiology, Graduate School of Public Health, University of Pittsburgh

Thesis Director: Jennifer J Adibi MPH, ScD, Assistant Professor, Department of Epidemiology, Graduate School of Public Health, University of Pittsburgh

Jennifer Adibi MPH, ScD

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ABSTRACT

Preeclampsia is one of the leading contributors to morbidity and mortality for both the mother and fetus. Risk factors include African-American ancestry, obesity, and high levels of allostatic load. Low socioeconomic status is associated with high allostatic load. We assessed the relationship between socioeconomic status and race in efforts to obtain an accurate estimation of the African-American risk of preeclampsia. This study is significant to public health because it may identify reasons behind the differences in preeclampsia risk of preeclampsia between African-American women and Caucasian women to reveal points of intervention to reduce this risk. Nulliparous Pittsburgh women who delivered singleton births at UPMC Magee Women's Hospital between Jan 1st 2007-Dec 31st 2014 were randomly sampled. Women with preexisting hypertension, diabetes, and thyroid disorder were excluded. Our final sample consisted of 527 cases and 1713 controls. We created multi-level regression models to assess the risk of preeclampsia. We included neighborhood level information provided by the 2009-2013 American Community Survey, 2000, Decennial Census, and other Pittsburgh-wide organizations. UPMC Magee-Women's Hospital Obstetrical Maternal and Infant database provided individual level indicators. The neighborhood indicators included; percentage of households on SNAP, poverty rate, unemployment, median household income, percent greenery, crime rate, and economic and demographic growth between 2000-2009. Together these multi-level models could potentially illuminate the driving forces behind both neighborhood

characteristics and individual qualities on the observed racial disparities in preeclampsia. Univariate analysis showed that African-Americans were more likely to have preeclampsia than Caucasians. When applying a multi-level model, the African-Americans odds decreased 16%. Under conditional regressions where neighborhoods were matched on similar quartiles of SNAP, poverty status, unemployment, and median household income, African-Americans odds of preeclampsia declined by 39-41%. The matched analysis explained more of the variability in risk of preeclampsia that was independent of race. Analysis of African-Americans compared to Caucasians indicated disparities among several neighborhood-level indicators. We discovered that the inclusion of the neighborhood environment explained some of the African-American risk of preeclampsia. We also noticed neighborhood-level disparities between Caucasians and African-Americans in Pittsburgh. We speculate the frequency of preeclampsia in African-Americans may be reduced by lowering these economic disparities.

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PREFACE

I would like to thank Karen Derzic, Mei Yang, and Dr. Janet Catov for their help in providing access to the MOMI data that was used for this analysis. I would also like to extend my thanks to Dr. Fabio in providing information regarding crime in the City of Pittsburgh from the Consortium for Injury Research and Community Action. I would also like to thank the SWPA Community Profiles for providing select Census demographic data.

I appreciate the guidance and reassurance from members of my Masters thesis committee. Thank you Drs. Adibi, Mendez, and Roberts.

1.0 INTRODUCTION

Preeclampsia is an adverse pregnancy outcome that results from endothelial injury and reduced maternal systemic perfusion and reduced blood flow to the placenta (1) complicating between three to seven percent of pregnancies in developed countries (2) . Preeclampsia is usually presented by high blood pressure (140/90 mmHg), and high protein content in the urine, although other manifestations may present themselves.

There are several diverse risk factors for preeclampsia, including, obesity (3-5), pre-gestational diabetes (3, 5, 6), hypertension (5, 6), thyroid issues (7, 8) nulliparity (5, 6), familial history of preeclampsia (9), previous diagnosis of preeclampsia (10), and African-Americans ancestry (5, 11, 12).

Preeclampsia is one of the leading causes of morbidity and mortality for both the mother and fetus (13, 14) during pregnancy. Women who have had preeclampsia are also at an increased risk of cardiovascular disease later in life (2, 15). Specifically, women with preeclampsia are at a three to four-fold increased risk of chronic hypertension, and two times as likely to suffer from ischemic heart disease or a cerebral infarction (16). They also have an increased risk of overall mortality compared to normal pregnancy (17). Women with preeclampsia are also at an increased risk of developing metabolic syndrome later in life (15, 17, 18). Children who are born to mothers with preeclampsia can suffer from several complications. These include intrauterine growth restriction, where the fetus does not appear to have achieved its genetic growth potential. The only cure for preeclampsia is the removal of the placenta and delivery, and if performed before 37 gestational weeks the baby is born prematurely with attendant morbidity. These abnormalities could affect child development, and could cause severe health problems later in life (13, 14). Efforts to reduce preeclampsia will not only benefit maternal health, but child development and health, as well.

Epidemiologists have cited that preeclampsia has been on the rise (19), and researchers believe socioeconomic status to be a contributor. One of the factors related to preeclampsia may involve stress (20). There are several negative outcomes from maternal stress during fetal development, including preterm birth and small for gestational age (21-23). The "weathering hypothesis" suggests that African-American women suffer from the deterioration of health as a response to constant chronic stress endured from social and economic adversities (24). Allostatic load has often been used to measure the effects of chronic stress (24-26). It is a compiled from biomarkers, such as HDL, LDL, CRP, IL-6, TNF-α, fasting plasma glucose, and other markers of inflammation, and cellular function. Typically, individuals with higher allostatic loads have poorer health compared to individuals with lower allostatic loads (26). Women in Pittsburgh with higher allostatic loads have been shown to have increased risk of preeclampsia (27). We propose to examine the relationship between neighborhood-level SES as a surrogate for stress and preeclampsia.

Studies that examine SES in association with reproductive health outcomes typically focus on individual level characteristics such as maternal education, household income, and employment status. We believe that these indicators do not encompass SES entirely, and overlooks neighborhood exposures. Models that include neighborhood indicators, such as poverty rate, crime rate, and neighborhood greenery represent SES from a population standpoint.

When modeled correctly this may efficiently tease apart the relationship between race and SES with disease risk. These results may reveal reasons for the disparity between Caucasian and African-Americans. This was a primary aim of this project.

The population of Pittsburgh has historically suffered from health disparities by race. In Allegheny County 2008-2012 estimates, Caucasians had an infant mortality rates of 4.75/1,000, while African-Americans had an infant mortality rates of 13.73/1,000 (28). Essentially African-Americans were almost 3 times more likely to have a child die within their first year of life. Considering the explicit infant death disparity in Pittsburgh between African-Americans and Caucasians, we were similarly interested in this disparity concerning race and preeclampsia.

This study is significant to public health because it may identify reasons behind the differences in preeclampsia risk among African-American and Caucasian women and reveal possible points of intervention to reduce the risk. We divided this paper into three aims, each with specific questions regarding to neighborhood, race, and preeclampsia: 1) Does inclusion of group-level information on neighborhood, as opposed to individual factors alone, help to explain the African-American risk of preeclampsia? 2) How influential are neighborhood economic factors on the risk of preeclampsia? 3) Do neighborhood factors have different effects on the risk of preeclampsia, judging by differences in direction, magnitude and significance, among African-Americans versus the rest of the population?

2.0 MATERIALS/METHODS

2.1.1 Study Population

72,000 to 80,000 births were delivered at UPMC Magee-Womens Hospital between Jan 1st2007-Dec 31st 2014. We randomly selected nulliparous women who resided within the city of Pittsburgh between the ages of 18-42 delivering singleton births during these eight years. In addition to the inclusion criteria, women who have had previous a diagnosis of hypertension, diabetes, or a thyroid disorder were excluded as these diseases, are known risk factors to preeclampsia. Our final sample consisted of 2240 women, where 527 were cases and 1713 were controls.

We selected cases and controls from UPMC Obstetrical Maternal and Infant (MOMI) database, a registry, which includes extensive measures of maternal diseases, her behavioral characteristics and demographics, as well as the information on infant health.

This population represented both mild and severe cases of preeclampsia as to capture as many women as possible. They were diagnosed by ICD-9 codes 642.4 (mild preeclampsia) and 642.5 (severe preeclampsia). Severity of preeclampsia based on gestational age was not optimal because there were only 36 women with preeclampsia delivered before 34 gestational weeks, which caused an inability to estimate differences in risk factors. All research has been approved by the Institutional Review Board of University of Pittsburgh.

2.1.2 Variables

2.1.2.1 Neighborhood-Level

Neighborhood Definition

Neighborhoods were defined by the 2010 Census Tract Boundaries, and the data was provided by the City of Pittsburgh's Department of City Planning. According to the US Census Bureau, census tracts are stable subdivisions of a county and generally have an average population between 1,200 and 8,000 people (29). 130 of the 138 Pittsburgh census tracts were represented in this population. The average 2009 population estimates in census tracts within the city of Pittsburgh was 2,240 people. The average area of the census tract was 0.40 square miles. The current literature uses census tracts as neighborhood definition, because of the easily accessible data for each individual census tract (30, 31).

Greenspaces

Data was acquired through the City of Pittsburgh's Department of City Planning. Overlaying their data with the 2010 census tracts, allowed for the calculation of the square mileage of parks, greenways, woodlands. A greenway is any land that is a part of an urban setting that is set aside for recreational use or environmental protection (32). A woodland is defined as is a low-density forest forming open habitats with plenty of sunlight and limited shade (33). The square mileage per census tract for parks, woodlands and greenways were calculated by ArcGIS (34). These total sums for each category were summed together and divided over the total square mileage of the census tract to assign each subject the percentage greenery, as their exposure.

Crime Rate

We gathered crime data through the Pittsburgh LINCS database. Violent crime is defined by four types; murder, rape, robbery, and aggravated assault (35). We calculated all violent crime was by the total number of crimes within each census tract per year from 2007 to the most recent available data, which was 2011. For mothers delivering between 2007 and 2010, we used the number of crime incidents that occurred within their census tract from 2007. For mothers delivering from 2011 to 2014, we used the number of crime incidents that were committed within their census tract from 2011. This database is a product of the Consortium for Injury Research and Community Action.

Median Household Income/Unemployment rate/Total Population

Median household income was taken from both the 2000 Census as well as the 5 year American Community Survey (ACS) 2009-2013 estimates using the Southwestern Community Profiles. Strengths of using ACS data is the up to date sampling frame provided by the US postal service's address canvassing. The responses are self-report, however, a select sub-sample are followed up with personal interviews. Limitations with using the 2000 Census information is the use of personal interviews with paper only responses, which creates a source of bias, making it less reliable compared to ACS data who use computer-assisted telephone and computer-assisted phone interviews as a method of follow-up. (36).

Unemployment was taken from the 2009-2013 ACS's estimates and the 2000 Census. Estimates of unemployment are based on responses to the questionnaire involving employment. Unemployment is defined as an able-bodied person who is 16 and over, is not currently working and has been seeking for employment within the past 4 weeks. Limitations with this include individuals who have been unemployed for more than 4 weeks are miscounted (37).

Total Population per census tracts were taken from the ACS 2009-2013 estimates and 2000 Census. The 2009-2013 population estimates were divided by each census tracts total square mileage to calculate the population density.

Change in Neighborhoods

The change in median household income, unemployment, and population was calculated by using 2009-2013 ACS estimates and 2000 Census data. These changes were used to represent neighborhood vitality through economic and demographic changes. Median household income change was termed as economic shift from 2000: income, unemployment change was termed as economic shift from 2000: unemployment, and population change was termed as demographic shift from 2000: population.

SNAP Household /Poverty Status

The Supplemental Nutrition Assistance Program (SNAP) is the federal program that was formerly the Federal Food Stamps program. Eligibility for SNAP is based off a standard that is related to the poverty level of the given state. County level estimates are initially based off the month of July, but then controlled with the state level SNAP. State estimations use a 12 month average, which smooths out abnormalities and excludes outliers that are a result of issues not relating to income (i.e disasters) (38).Count data for total households and households on SNAP for each census tract was taken from the 5 year ACS 2009-2013 estimates using the American Fact Finder. Those on SNAP were divided over the total household count to give the percentage of households on SNAP within the census tract. These indicators were used as another income-based measurement.

Poverty is defined by the US Census as a family's total income below a computed threshold. The threshold is determined by the size of the family and the age of its members. There are a total of 48 different thresholds throughout the US and do not differ geographically (39). The total income of a family is determined by earnings before taxes and excludes non-cash benefits, like SNAP benefits, and capital gains. Data from the 5 year ACS 2009-2013 provided each census tract with the percentage of households below the poverty threshold. These indicators were used as another income-based measurement. Neighborhood indicators, except crime rate, used percentages instead of count data because of the interpretability from the result. This is consistent with literature (40, 41).

2.1.2.2 Individual–Level

Individual level variables that were adjusted for in the models to estimate the risk of preeclampsia include race, maternal age, maternal education level, method of payment, and marital status, which were provided through the MOMI database.

2.1.2.3 Covariates

Covariates that were evaluated as potential confounders included pre-pregnancy BMI, smoking status, asthma status, cervical and uterine abnormalities, virus or bacterial infection, and total number of pregnancies and abortions were provided through the MOMI database.

2.2 STATISTICAL ANALYSIS

Descriptive Analysis:

First, we compared the distribution of all exposures among the cases and controls using chi-square test and t-tests where appropriate. All significant values were determined to be below alpha=5%. All neighborhood indicators were categorized to quartiles to enable better analysis and interpretability across neighborhoods with similar characteristics.

Population differences among the census tracts were considered by including population density to the models to control for smaller, or less populated neighborhoods. All statistical analyses were performed by SAS 9.4 (42). Spatial maps created in ArcGIS showed the distribution of cases amongst census tracts in the City of Pittsburgh.

Aim 1: Analyze the relationship between race and the risk of preeclampsia, before and after adjusting for individual and neighborhood-level factors

We first analyzed the effects of neighborhood indicators on the observed differences in preeclampsia between African-Americans and Caucasians. We restricted the population to include African-Americans and Caucasians. We used PROC LOGISTIC to model the effects of individual level indicators on preeclampsia. PROC GLIMMIX was used to assess the effects of neighborhood factors has on the race effect of preeclampsia. We used a step-forward model synthesis method, where we modeled each indicator individually, and choose the model with the lowest log-likelihood. (**See Appendix, 7B**), a final model was constructed that included race, the economic growth from 2000: income, percent greenery, crime rate, as well as, controlling for BMI before pregnancy because of its strong predictive association with preeclampsia. Covariates used in the logistic regression, which were smoking status (yes/no) illnesses, viral or bacterial infection, and any uterine or cervical abnormalities, were not included in the neighborhood models, because they do not fit the criteria for a confounder as a common cause of neighborhood-related stress and preeclampsia risk. Both individual and neighborhood variables were treated as fixed effects and the census tracts were treated as a random effect.

Additionally four models used conditional logistic regression, where PROC LOGISTIC was used to match patients on similar quartiles of the four neighborhood income indicators. The conditional regression models used on SNAP, poverty status, unemployment, and median household income to match subjects. Our rationale for the matched analysis in the absence of census tract grouping was an “artificial” desegregation of African-Americans and Caucasians to see if risk estimates would change. This method combined the 130 represented census tracts to four theoretical neighborhoods. This method increased the power by increasing the number of women in each theoretical neighborhoods and with more women the heterogeneity increased. These models were individually adjusted for maternal age, marital status, insurance method, greenery, crime, population density, BMI before pregnancy, and economic shift from 2000: income. When matching on median household income, demographic shift from 2000: population was used instead because of a better model fit.

Aim 2: Analyze the relationship of neighborhood indicators of poverty and preeclampsia

This aim explored the association between neighborhood economic indicators and the risk of preeclampsia, and how they changed with the addition of individual and neighborhood factors. PROC GLIMMIX was used to assess the association between the neighborhood level-income variables, where both individual and neighborhood variables were treated as fixed effects and the census tracts were treated as a random effect. The four neighborhood economic indicators were highly correlated, and were used in separate models to prevent over adjustment (**See Appendix B, 8B**). Similar multi-level step-wise model building was used for each of the four neighborhood indicators. We used a step-forward model synthesis method, where we modeled each indicator individually, and choose the model with the lowest log-likelihood (**See Appendix B, 9B-12B**). Sequential model building was implemented using other neighborhood and individual level covariates to observe the specific change the specified neighborhood economic indicator had on preeclampsia. SNAP, poverty status, and unemployment individually used economic shift from 2000: income, crime rate and percent greenery in their final models, while median household income used demographic shift from 2000: population, crime rate and percent greenery in the adjusted model. We also included race in the adjusted model as the third and final model. We also wanted to observe the shape of the neighborhood exposure-preeclampsia risk relationship by modeling linear and quadratic trends.

Aim 3: Assess differences by race in the association of neighborhood level factors and the risk of preeclampsia

The last analysis assesses whether the relationship between neighborhood exposures and preeclampsia differs by race. We stratified the sample by race and calculated the averages for cases and controls. (1210 Caucasian, 673, African-American, 208 Other). 149 women had missing information on race and were not included in this last aim. T-tests determined the significance between cases and controls of each respective race. Further analysis explored interaction effects between the neighborhood indicators and race with risk, where we modeled the neighborhood indicator, race and an interaction term between the two. We were also interested with interaction effects between BMI and race with risk. Significance of the interaction term was determined by the p-value ($p<0.05$) taken from the type III effects.

3.0 RESULTS

There were distinct differences between cases and controls. Cases were younger, lived in census tracts with lower median household, higher unemployment rates, higher households on SNAP benefits, higher rates of poverty and higher crime rates. Fewer cases were married (37%) than controls (52%) and more cases (45%) were on medical assistance than controls (32%). In this population, African-Americans were 28% of controls, and were 44% of cases. See **Table 1 and Table 2,** for further distributions. Maps provided in **Appendix A** show the neighborhoods most represented in this study, as well as, the distribution of cases within the study population.

Table 1: Descriptive Characteristics for Pittsburgh MOMI Sample between 2007-2014 (n=2240) and p-values for the differences between women with vs. those without preeclampsia.

Continuous variables	Controls mean (range)	Cases mean (range)	p-value
Maternal age	27.6 (18-42)	26.6 (18-42)	0.0003
BMI before pregnancy	24.2 (14.1-45.8)	25.6 (14.1-45.8)	<.0001
Percent Unemployment	4.7% (0-14%)	5.4% (0-14%)	<.0001
Percent SNAP (food assistance)	16% (0-60%)	20% (0-60%)	<0.0001*
Percent Below Poverty	21% (0-86%)	23% (0-86%)	0.0015*
Median Household Income at 2009	$42,576 ($10,604-$83,690)	$39,175 ($10,604-$83,690)	<.0001
Percent Greenery	16% (0-93%)	16% (0%-93%)	0.1247*
Crime rate for indicator year (2007, 2011)	16 (0-65)	18 (0-65)	0.0004*
Economic shift from 2000: income	37% (-27%, 165%)	34% (-27%, 159%)	0.0574
Economic shift from 2000: unemployment	41% (-83, 324%)	34% (-83%, 324%)	0.7937
Demographic shift from 2000: population	-7% (-54%, 51%)	-9% (-54%, 51%)	0.0435

**Wilcoxon ranked sum test*

Table 2: Categorical Distributions for Pittsburgh MOMI Sample between 2007-2014 (n=2240) and p-values for the differences between women with vs. those without preeclampsia.

Categorical variables	Control N (%)	Case N (%)	p-value
Marital Status			<.0001
Divorced	11(0.6)	2 (0.4)	
Married	894 (52)	196 (37)	
Single	778 (45)	320 (61)	
Unknown	24 (1)	7 (1)	
Separated	6 (0.4)	2 (0.4)	
Race			<.0001
Caucasian	960 (60)	250 (50)	
African-American	450 (28)	223 (44)	
Other	179 (11)	29 (6)	
Maternal Education			<.0001
<High School	110 (7)	36 (8)	
GED (high school certificate)	295 (20)	136 (29)	
>High School	284 (19)	105 (22)	
College	371 (25)	95 (20)	
Post-grad	423 (29)	96 (21)	
Insurance			<.0001
Medical Assistance	551 (32)	238 (45)	
Private	1160 (68)	287 (54)	
Self-Pay	2 (0.1)	2 (0.4)	

Aim 1: Analyze the relationship between race and the risk of preeclampsia, before and after adjusting for individual and neighborhood-level factors

Table 3: Logistic Regression Evaluating Individual-Level Risk of Preeclampsia

Variable	Odds Ratio	L95	U95
African-American (unadjusted)	**1.90**	**1.54**	**2.35**
African-American (adjusted)	**1.59**	**1.18**	**2.16**
Age	**1.04**	**1.01**	**1.10**
Below HS vs GED	0.63	0.39	1.00
Some HS vs GED	0.86	0.62	1.20
College vs GED	0.81	0.52	1.25
Post-BA vs GED	0.73	0.44	1.21
Medical Assistance vs Private	1.31	0.95	1.79
Self-Pay vs Private	2.52	0.20	31.38
Obese vs Normal	**1.60**	**1.12**	**2.29**
Overweight vs Normal	1.19	0.89	1.60
Divorced vs Married	0.43	0.05	3.62
Separated vs Married	1.64	0.29	9.16
Single vs Married	**1.49**	**1.03**	**2.17**
Unknown vs Married	1.41	0.51	3.88

The model was adjusted for smoking status (Yes/No), asthma, uterine/cervical abnormalities, virus/bacterial infection and total number of terminations/pregnancies

In Aim 1 we explored the contribution of individual and neighborhood factors to the increased risk of preeclampsia in African-Americans. In an unadjusted model (**Table 3, Top**), African-Americans were almost twice as likely to develop preeclampsia compared to Caucasians. Adjusting for individual factors (**Table 3, Bottom)**, decreased the odds among African-American women by 31%. Maternal age, marital status, obesity, and race were significant predictors of preeclampsia, while maternal education status was not.

Table 4: Multi-level Mixed Model and Conditional Logistic Regression Evaluating the Effect Neighborhood Environments has on the Race Effect of Preeclampsia

Multi-level Model		**Odds Ratio**	**95% Confidence Interval**	
African-American vs. Caucasian (univariate)		**1.85**	1.49	2.30
African-American vs. Caucasian (adjusted)		**1.69**	1.29	2.21
adjusted for economic growth: income, % greenery, crime rate, body mass index				
Matched analysis (logistic regression)[1]				
Matched Factor (Quartiles)				
SNAP	***African-American vs. Caucasian***	**1.50**	1.08	2.08
% Poverty status		**1.50**	1.09	2.06
Unemployment		**1.50**	1.09	2.05
Median Household Income[2]		**1.52**	1.10	2.10

[1] adjusted for age, insurance, marital status, % greenery, change in median household income, crime, BMI before pregnancy
[2] change in population was used instead of change in median household income

In a multi-level model, we controlled for between and within-census tract correlation in geographically distributed measures of neighborhood. (**Table 4)** The univariate estimate indicated that African-Americans were still almost twice (OR 1.85 95% CI (1.49, 2.30)] as likely to develop preeclampsia compared to Caucasians. The final adjusted model reported that African-Americans odds decreased by 16%. This indicated that about 19% of the variability in the observed African-Americans risk could be explained by the inclusion of the information on neighborhood environment.

We matched subjects by their neighborhood characteristics including quartiles of SNAP benefits, poverty status, unemployment rate, and median household income. African-Americans were more likely to have preeclampsia compared to Caucasians in all four models [OR 1.50 95% CI (1.08, 2.08) OR 1.50 95% CI (1.09, 2.06) OR 1.50 95% CI (1.09, 2.05) OR 1.52 95% CI (1.10, 2.10), respectively].

Using this modeling strategy, the initial univariate risk decreased from 85% to 50% and 52%. This means that the inclusion of the neighborhoods matched on median household income, SNAP benefits, poverty status, and unemployment rate, explained 39-41% of the variability in the African-American risk of preeclampsia.

Aim 2: Analyze the relationship of neighborhood indicators of poverty and preeclampsia

Table 5: Multi-level Mixed Model Evaluating the Effect Neighborhood Environments has on Risk of Preeclampsia

Neighborhood Income	Quartile	Unadjusted OR (95% CI)	Model 1 OR (95% CI)	Model 2 OR (95% CI)
SNAP	Lowest (Ref)	1.0	1.0	1.0
	2	1.28 (0.95, 1.74)	1.07 (0.73, 1.56)	1.01 (0.68, 1.49)
	3	1.34 (0.97, 1.84)	1.35 (0.93, 1.96)	1.24 (0.83, 1.85)
	Highest	**2.06 (1.53,2.78)**	**1.89 (1.26, 2.82)**	1.36 (0.87,2.15)
Linear trend (*p-value*)		0.518	0.819	0.904
Quadratic trend (*p-value*)		**0.0004**	**0.003**	0.111
Poverty Status	Lowest (Ref)	1.0	1.0	1.0
	2	1.125 (0.84, 1.5)	1.10 (0.80, 1.53)	1.06 (0.75. 1.49)
	3	1.2 (0.90, 1.6)	1.14 (0.82, 1.6)	1.09 (0.77, 1.55)
	Highest	**1.64 (1.24, 2.16)**	**1.64 (1.15, 2.35)**	1.38 (0.93, 2.04)
Linear trend (*p-value*)		0.924	0.891	0.899
Quadratic trend *(p-value)*		**0.006**	**0.042**	0.205
Unemployment Rate	Lowest (Ref)	1.0	1.0	1.0
	2	1.08 (0.80, 1.48)	1.34 (0.94, 1.9)	1.31 (0.90, 1.89)
	3	1.27 (0.94, 1.71)	1.41 (0.98, 2.01)	1.35 (0.93, 1.96)
	Highest	**1.71 (1.28, 2.30)**	**1.98 (1.37, 2.88)**	**1.62 (1.09, 2.42)**
Linear trend (p-value)		0.905	0.349	0.287
Quadratic trend *(p-value)*		**0.001**	**0.005**	0.064
Median Household* Income	Lowest (1.0)	1.0	1.0	1.0
	2	**0.67 (0.51, 0.88)**	0.70 (0.48, 1.02)	0.82 (0.55, 1.22)
	3	**0.71 (0.54, 0.94)**	0.73 (0.49, 1.07)	0.94 (0.62, 1.42)
	Highest	**0.53 (0.40, 0.70)**	**0.51 (0.34, 0.77)**	0.65 (0.42, 1.02)
Linear trend (*p-value*)		**0.037**	0.214	0.699
Quadratic trend *(p-value)*		**0.008**	**0.027**	0.346

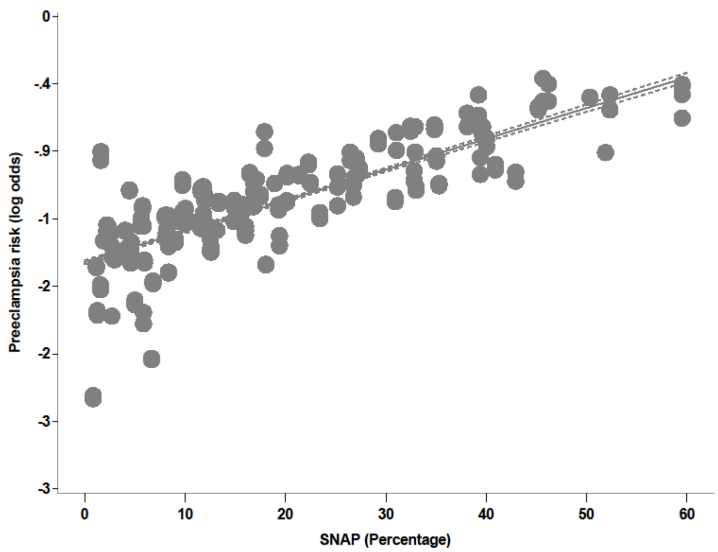
Model 1 adjusted for Economic Shift from 2000: Income,% Greenery, Crime Rate;
Model 2 adjusted for (1)+Race;
* Demographic shift from 2000: population substituted Economic Shift from 2000: Income

In Aim 2 we asked, "How influential are neighborhood factors on the risk of preeclampsia?" In a univariate analysis, (**Table 5**) women who lived in the neighborhoods with the highest quartile of households receiving SNAP, poverty status, unemployment rate, and median household income had a 2.06, 1.64, 1.71, and 0.53 odds, respectively, of developing preeclampsia compared women who lived in neighborhoods with lowest quartile.

In the adjusted models that do not include race, women who lived in the neighborhoods with the highest quartile of households receiving SNAP, poverty status, and unemployment rate, and median household income had a 1.89, 1.64, 1.98, and 0.51 odds, respectively, of developing preeclampsia compared women who lived in neighborhoods with lowest quartile. When adding race to the models, the only income indicator to remain significant was unemployment.

We looked for trends in the results and discovered that all four indicators had significant trends when adjusting for neighborhood environment, however, when we added race to the models, these trends disappear. Even though we report quartile estimates in Table 5, we plotted the neighborhood exposures as continuous variables to illustrate the change in the relationship after adjustment of race in **Figures 1-4. Panel A** represents the adjustment of neighborhood factors and **Panel B** represents the inclusion of race. The addition of race drastically weakened each correlation. The direction of "Other" in **Figure 3b** reversed after the addition of race. We believe this aim strongly supports the strength of race as a true confounder of the relationship between neighborhood environment and the risk of preeclampsia in our sample.

a)



b)

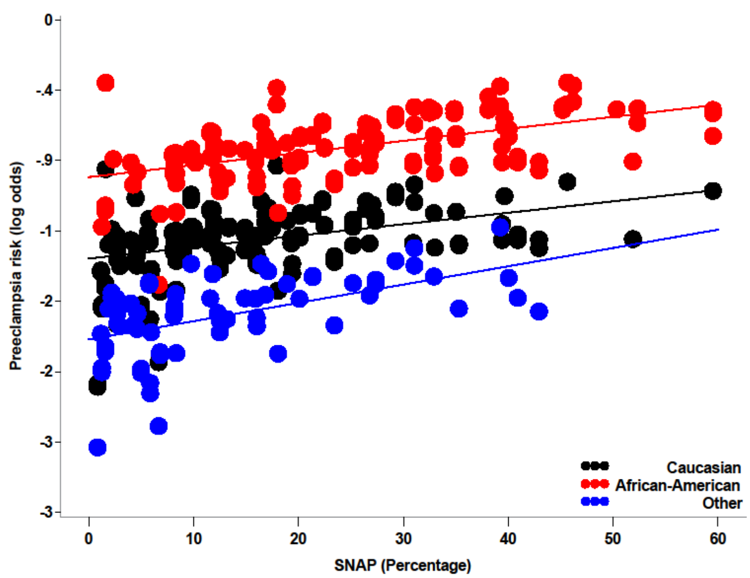
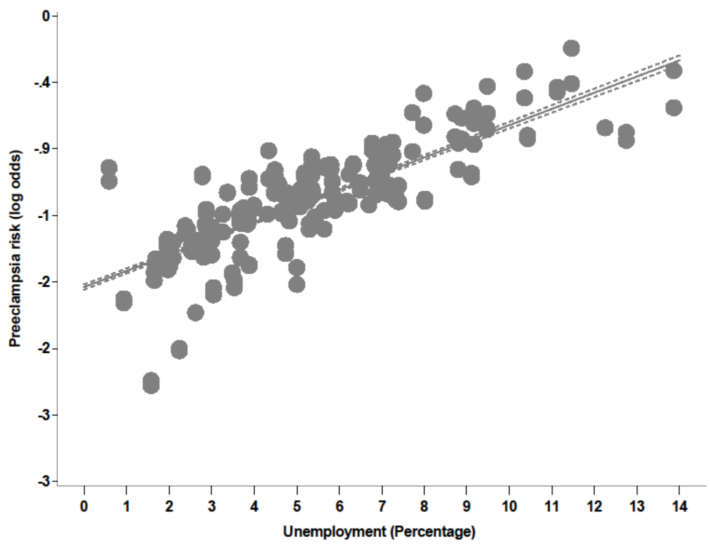


Figure 1: The association of SNAP with the log odds of preeclampsia risk among women in Pittsburgh, and evidence of confounding by race
a) unadjusted for maternal race b) adjusted for maternal race

a)



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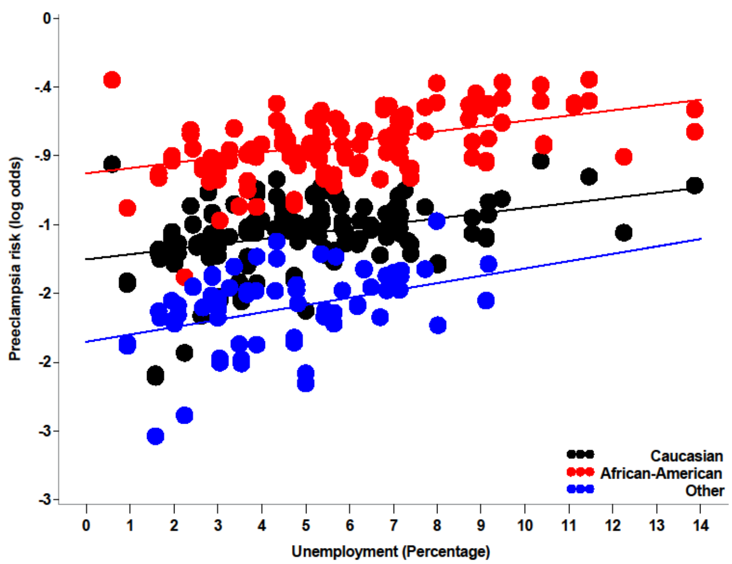
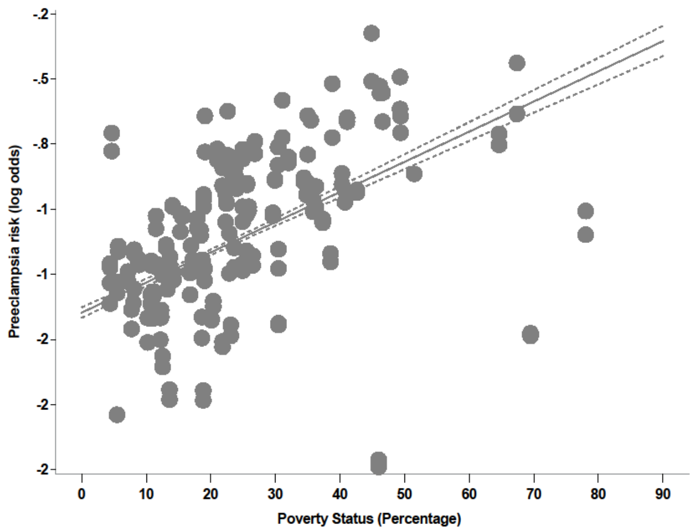


Figure 2: The association of unemployment with the log odds of preeclampsia risk among women in Pittsburgh, and evidence of confounding by race
a) unadjusted for maternal race b) adjusted for maternal race

a)



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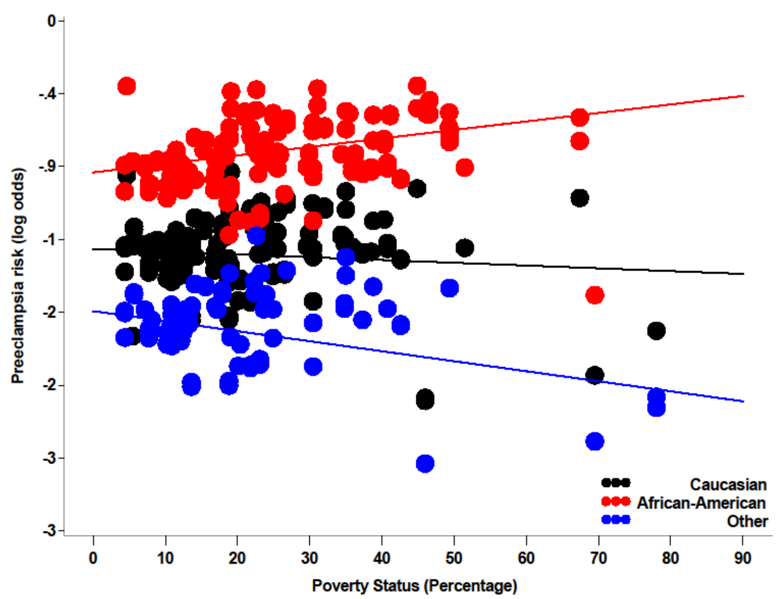
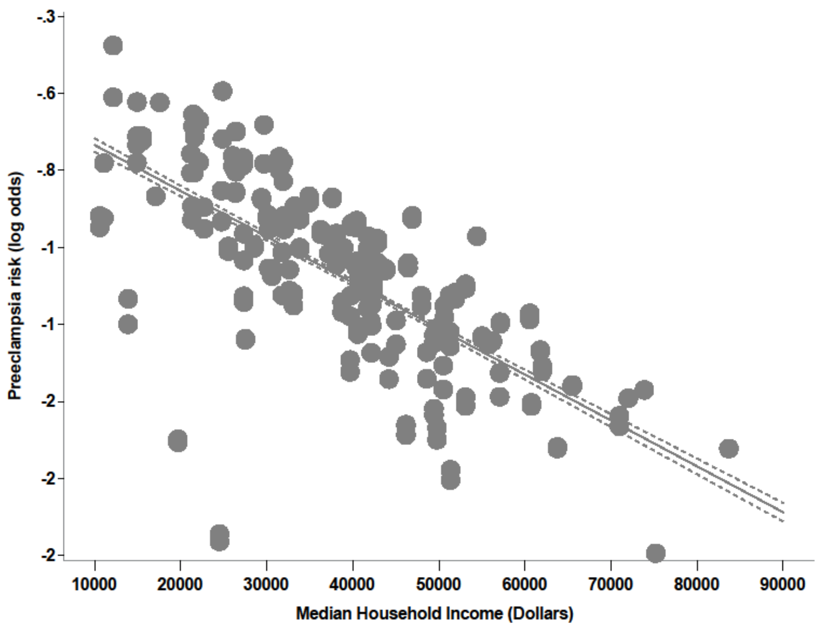


Figure 3: The association of poverty status with the log odds of preeclampsia risk among women in Pittsburgh, and evidence of confounding by race.
a) unadjusted for maternal race b) adjusted for maternal race

a)



b)

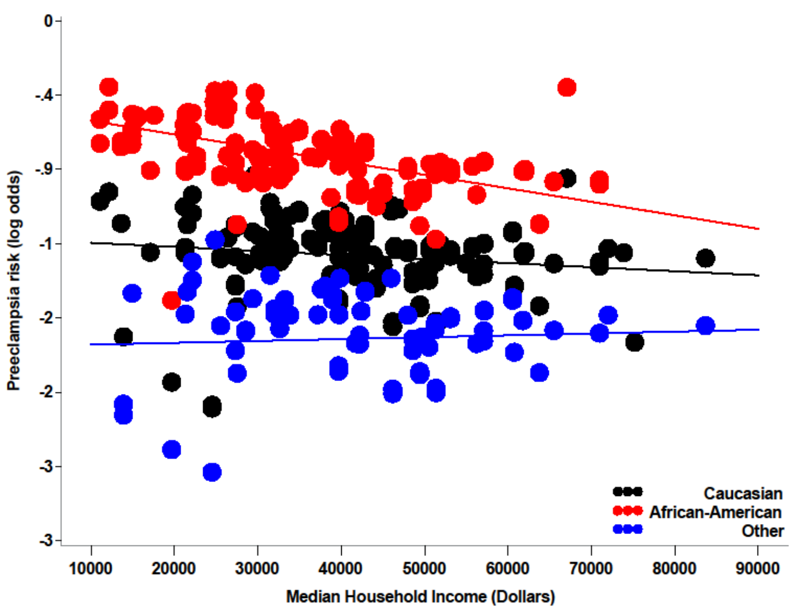


Figure 4: The association of median household income with the log odds of preeclampsia risk among women in Pittsburgh, and evidence of confounding by race
a) unadjusted for maternal race b) adjusted for maternal race

Aim 3: Assess differences by race in the association of neighborhood level factors and the risk of preeclampsia

Table 6: Averages of Neighborhood Indicators Stratified by Race

	African-American			**White**			**Other**		
Variables	*Cases (N=223)*	*Controls (N=450)*	*p-value*	*Cases (N=250)*	*Controls (N=960)*	*p-value*	*Cases (N=29)*	*Controls (N=179)*	*p-value*
Greenery (%)	17	17	0.745	16	17	0.667	12	9	0.212
Unemployment (%)	7	7	0.998	5	4	***<0.01***	5	4	0.107
Snap (%)	29	28	0.370	13	13	0.484	15	10	***0.019***
Below Poverty (%)	30	30	0.938	19	18	0.212	22	22	0.954
Median Household Income at 2009	$31,156	$32,054	0.382	$45,607	$47,094	0.114	$41,159	$44,012	0.331
Economic Shift from 2000: Income (%)	29	26	0.242	39	40	0.588	31	36	0.282
Economic Shift from 2000: Unemployment (%)	34	40	0.388	44	46	0.716	17	23	0.682
Demographic Shift from 2000: Population (%)	-18	-17	0.581	-5	-6	0.467	-5	-4	0.488
Crime Rate	24	23	0.426	13	13	0.436	15	13	0.330

Aim 3 explored the relationship between race and neighborhood indicators. Several categories demonstrated evident differences between cases and controls. Percent unemployment, percent SNAP, and crime were higher than their control race counterpart. Median household income was distinctly lower in the cases compared to their counterpart. In **Table 6**, we show the respective average of each indicator within the women's race and case status. Statistical tests of comparisons were calculated, and unemployment rates were significantly different between

Caucasians, and the percentage household on SNAP were significantly different amongst others. This table also points out the disparities among the study population, citing the differences between white cases and African-American controls.

Table 7: Interaction Effects between Race and Select Variables on Preeclampsia

Variable	p-value	Variable	p-value
SNAP(cat)*race	0.3947	Unemployment(cat)*race	0.4132
SNAP(cont)*race	0.1623	***Unemployment(cont)*race***	***0.0321***
PS(cat)*race	0.9826	Greenery(cat)	0.8187
PS(cont)*race	0.5466	Greenery(cont)	0.4189
MHI(cat)*race	0.8001	***Crime rate(cat)*race***	***0.0318***
MHI(cont)*race	0.871	Crime rate(cont)*race	0.8849
Unemployment Change(cat)*race	0.3584	Pop Change (cat)*race	0.7191
Unemployment Change(cont)*race	0.8546	Pop Change (cont)*race	0.5263
MHI Change (cat)*race	0.5478	BMI pre-pregnancy(cat)*race	0.4524
MHI Change (cont)*race	0.2438	***BMI pre-pregnancy(cont)*race***	***0.0312***

Since neighborhood factors were shown to be different among the different races, we modeled interaction coefficients to test significance. **Table 7** shows the indicators in continuous and categorical forms. SNAP, unemployment rates and BMI were significant as continuous variables, while crime rate as a categorical variable was significant. We believe that the differences between continuous and categorical interactions are a result of residual confounding.

Figures 5 and **6** show the interaction plots between continuous unemployment rate, and BMI before pregnancy in estimating the log odds of preeclampsia. In both figures, women who identified as "Other" had the strongest association between the exposure and the outcome through unemployment rate, and BMI.

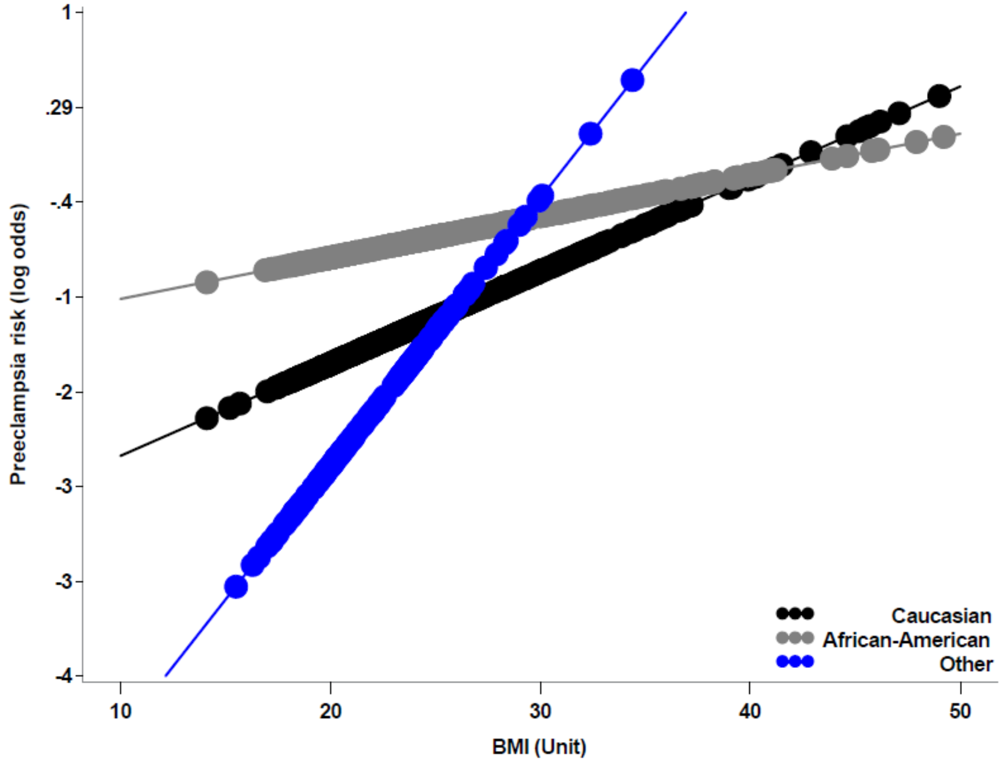


Figure 5: Interaction between race and BMI with the log odds of preeclampsia risk among women in Pittsburgh

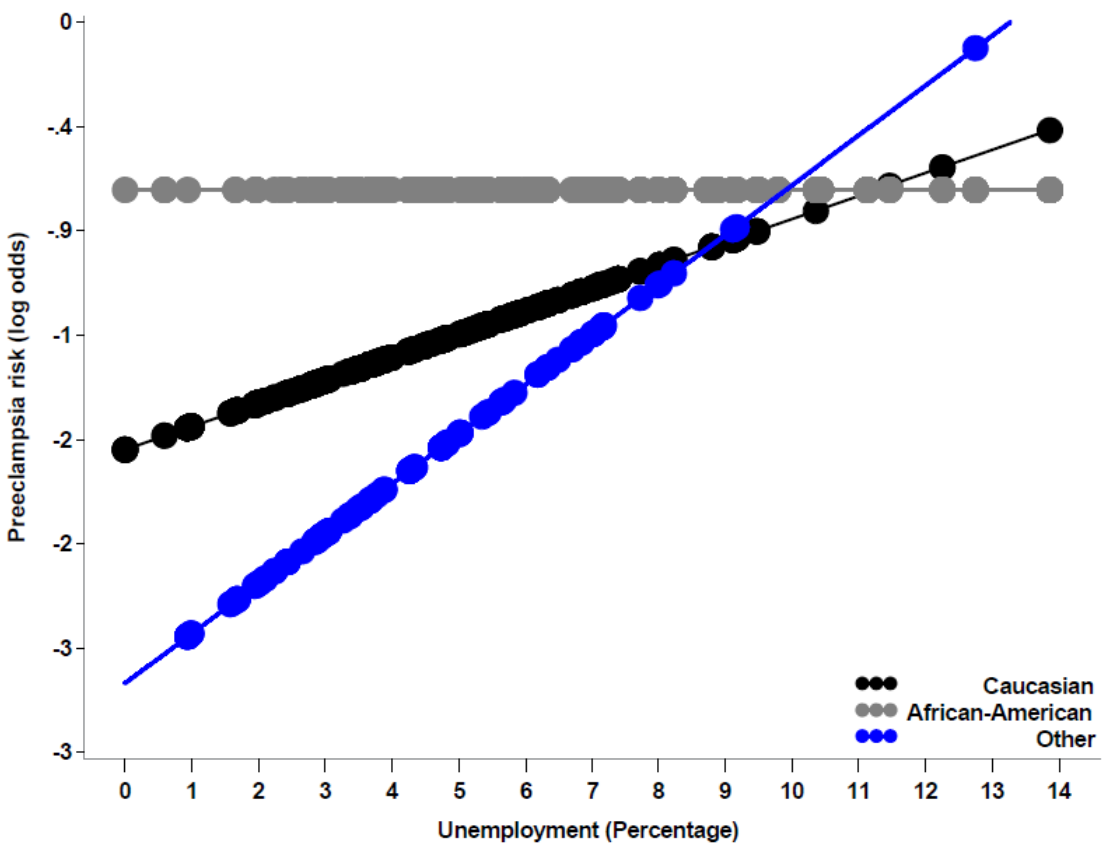


Figure 6: Interaction between race and unemployment with the log odds of preeclampsia risk among women in Pittsburgh

4.0 DISCUSSION

In this study, we proposed socioeconomic factors have a substantial impact on the risk of preeclampsia among African-American women in a city that is highly segregated by race and income. Our hypothesis was that neighborhood environment would describe more of the African-American risk than strictly using individual factors. We reported that neighborhood environment minimally explained the risk of preeclampsia among African-American women. We found that irrespective of neighborhood environment, race was a stronger predictor for preeclampsia within our study population. Lastly, we indicated that there were disparities in neighborhoods, regardless of case status, among African-Americans and the rest of Pittsburgh.

We discovered a 31% decrease in risk for preeclampsia among African-American women after the inclusion of individual factors. We also found that there was a 16% decrease in the association of race and the risk of for preeclampsia after the inclusion of the neighborhood environment. Although we expected this reduction to be greater, this was typical. A North Carolina study found similar results where neighborhood environment reduced the crude racial disparities of preterm birth by 15% (31). Other studies evaluating neighborhood inclusion have also found reductions in risk of adverse birth outcomes among African-Americans (43, 44). We were curious to see if manipulation of neighborhood definitions, through different statistical models, would result in a greater decrease

When applying conditional regressions we increased neighborhood diversity, and noticed a larger decrease in the association of race and risk for preeclampsia. Possible reasons for this may be from the larger sample size from combining 130 census tracts to four simulated neighborhoods, which increased the power. In addition to more power, the heterogeneity of the simulated neighborhoods increased because of the inclusion of more women. Other reasons may revolve around the intraclass correlation coefficient (ICC) of 1%, which indicated that there was greater variability within census tracts than across different census tracts. This brings to question the viability of census tracts as a neighborhood definition over other metrics that are used to define neighborhoods. The primary mixed-model demonstrated that neighborhood inclusion has some effect on the observed risk of preeclampsia among African-American women.

The large differences between the two methods on neighborhood inclusion led us to several questions. One question involved the selection of our indicators, however, they were purposely selected to represent various aspects of the socioeconomic environment. They can be broken down into distinct categories; neighborhood income, physical/ psychological, and overall neighborhood climate. The percentage of households receiving SNAP, the below poverty status rate, the unemployment rate, and the median household income represented four different measures of neighborhood income. The percent greenery was a surrogate for the physical activity, and psychological well-being of the neighborhood. The crime rate demonstrated another portion of psychological effects of the neighborhood. The changes in income, unemployment, and population indicated the vitality and climate of a neighborhood (45). The revitalizing of a neighborhood has several consequences where current residents are disadvantaged. Increases in rent and standard of living disrupt communities and disperses the residing population. Theses ramifications from gentrification lead to a great deal of stress and other negative health implications known as “root shock” (46).

There are several reasons as to why we found minimal reductions in the association of race and preeclampsia. Possible reasons for the 16% reduction in the primary multi-level model may have been a result the exclusion of attributing the nutrient availability and accessibility in her neighborhood, discrimination, early life exposures, housing quality, and multi-generational effects, as well as other similar attributes. Additional reasons for the small decrease may have been due to misclassification through the usage of aggregate census data for individual levels of exposure. Before analysis, we assessed the internal validity by plotting distributions of the indicators, in efforts to identify and drop potential outliers. We also increased internal validity by applying imputations where necessary to reduce the impact of missing data. These methods ensured that the controls represent the underlying population from which the cases arose.

We also wanted to explore the disparities in Pittsburgh. We showed that disparities still exist between African-American neighborhoods and the rest of the city. We also indicated the importance of race on risk of preeclampsia within this population by revealing the high African-American risk, independent of neighborhood environments. Women who live in neighborhoods with low socioeconomic status are at higher risk for adverse birth outcomes than women in wealthier neighborhoods. These include preterm birth, small for gestational age, and low birth weight (47, 48). Interestingly, the interaction plots show little effect on the risk of preeclampsia among African-American women with increasing unemployment, or BMI compared to Caucasian and Other women. Other studies have also indicated evidence of effect modification through low-income neighborhoods and race on preterm birth (49, 50). The remaining high rate of preeclampsia in African-Americans supported the idea of unmeasured stressors, such as segregation as a possible reason for the high relative odds.

Segregation has been associated with poor birth outcomes where women are at higher risk for birthweight, preterm birth and small for gestational age (30, 31). One particular study reported that independent of economic factors, racial segregation increased the risk of intra-uterine growth restriction within African-American women (51). Pittsburgh is located in the heart of the “Rust Belt.” The Pittsburgh area was primarily known as the epicenter for steel and coal production. When the steel industry began, it attracted African-Americans to migrate from the South to Pittsburgh for work (52). The steel industry was partly responsible for the creation of an African-American middle class in Pittsburgh. In conjunction with steel mills closing, among other reasons, the African-American middle class began to decline and over the years, this decline propagated increased segregation between Caucasians and African-Americans within the city (53).

We did not directly measure segregation, and a critical aspect that was missing from the models was individual-level experience of racism. Racism can be expressed blatantly or subtlety as institutionalized racism. There are several ways to measure blatant and institutionalized racism. An index of homeowner information through the Home Mortgage Disclosure Act (HMDA) can accurately detect redlining practices and estimate the effects of institutionalized racism (54). Residential redlining is bias by lending institutions against appropriations to minority groups (55). These practices have negative health effects on residents because of forced living conditions in an underserved area (54). Certain surveys like the Cohen Perceived Stress Scale, are validated metrics to measure a persons perceived stress, which can depict forms of blatant racism. Future studies of neighborhood environment and racial disparities should include direct, individual-level measurements of the experience and perception of racism because of the potential strength these factors have on the race effect and risk of disease.

Limitations with this study include missing data. Around 34% of information on pre-pregnancy weight was missing at random, a simple regression was imputed for all controls based on age and height of the mother. This method drastically reduced the number missing, but did not fill in the entire data set since information on height was also missing. Consequences of using a single imputation are the assumption of certainty with the values, which ultimately underestimated the standard errors and overestimates test statistics (56), which pushes away from the null.

Misclassification of preeclampsia diagnosis may also have been an issue. Many symptoms of renal or liver dysfunction may not present themselves and can often go unnoticed. Looser guidelines that are more inclusive from the American College of Obstetric Clinicians have been created to prevent misdiagnosis and include women who would otherwise have been missed (57).

There was no information on race in the group identified as “Other”. While the largest minority other than African-Americans in Pittsburgh are Asians, assuming the 208 women who identified as “Other” are all, or a majority, Asian would have been an incorrect assumption. Furthermore, women who may have identified as being more than one race would be considered as “Other”. This variable population has a high chance of heterogeneity and skews the ability to interpret the interaction results. We excluded this population from the first aim, and we believe that this did not compromise our overall results.

Usage of categorical variables may have possibility contributed residual confounding to the estimates, as these variables were initially continuous, but divided into four categories for easier interpretation. Some mediators were unmeasured, specifically acute stress biomarkers such as TNF-a, CPR, or cortisol. We did not have any measures of the placenta, which is the basis of preeclampsia. These measures would include pregnancy hormones, like hCG, PAPP-A, or AFP (58) may also have an effect in relation to both stress and preeclampsia. As discussed earlier, aspects of social structure, culture and communal effects were unmeasured and may be different among the different neighborhoods. These factors may play a role in either contributing or alleviating the risk of preeclampsia.

Despite these limitations, several strengths are present within this study. The population of the study helped narrow the hypothesis to only neighborhood and individual stress exposures and risk of preeclampsia. The exclusion of chronic hypertension, diabetes, and thyroid complications removed cases with strong causes of preeclampsia that were most likely not due to socio-economic status and related stress. Another strength of this study was the use of mixed models to better estimate the marginal effects of indicators in efforts to take into account the correlation between women within the same census tract. We realized after the fact that the within-census tract variation was extremely high (intraclass correlation coefficient 0.01). As we prepare to publish these findings, we will determine if this argues for a different modeling strategy. The novelty of this study is another strength. It is the first of its kind that looks at the effects neighborhoods have on the risk of preeclampsia within the city of Pittsburgh.

We propose to further explore the relationship between neighborhoods and race with risk of preeclampsia to include the addition of redlining practices, and food environment to the models. Low economic African-American neighborhoods often time have worse food environments than their Caucasian counterparts (55). We also would use buffer zones as neighborhood definitions, instead of census tracts, to obtain a more accurate risk estimate of neighborhoods. Other measurements can include indicators that define social/communal structure that could further untangle the interactions between race and SES. These elements may better delineate the effect of race on preeclampsia and provide specific targets for policy development to alleviate risk. Additional targets for research include usage of biomarkers that can quantify acute or chronic stress. Researchers could identify possible interactions between chronic stress and acute stress with its implications on preeclampsia. While not performed in this study, researchers could investigate the effects of African-Americans living amongst a majority of Caucasians, compared to Caucasians living amongst a majority of African-Americans. This could explore the hypothesis of the effects of segregation on risk that may explain the associated risk rather than strictly race and poverty.

In summary, it is evident that the inclusion of neighborhood indicators on preeclampsia explains some risk that is observed among African-American women. We believed that the increase in heterogeneity decreased the African-American risk substantially, and offer ideas for research and the implementation of policy to increase the diversity within neighborhoods. These policies may reduce the risk of preeclampsia and other health outcomes. These research methods performed in this study could also be applied to race, socioeconomic factors, and their relationship with other health risks.

APPENDIX A: MAP OF PITTSBURGH

Figure 7A: Neighborhoods

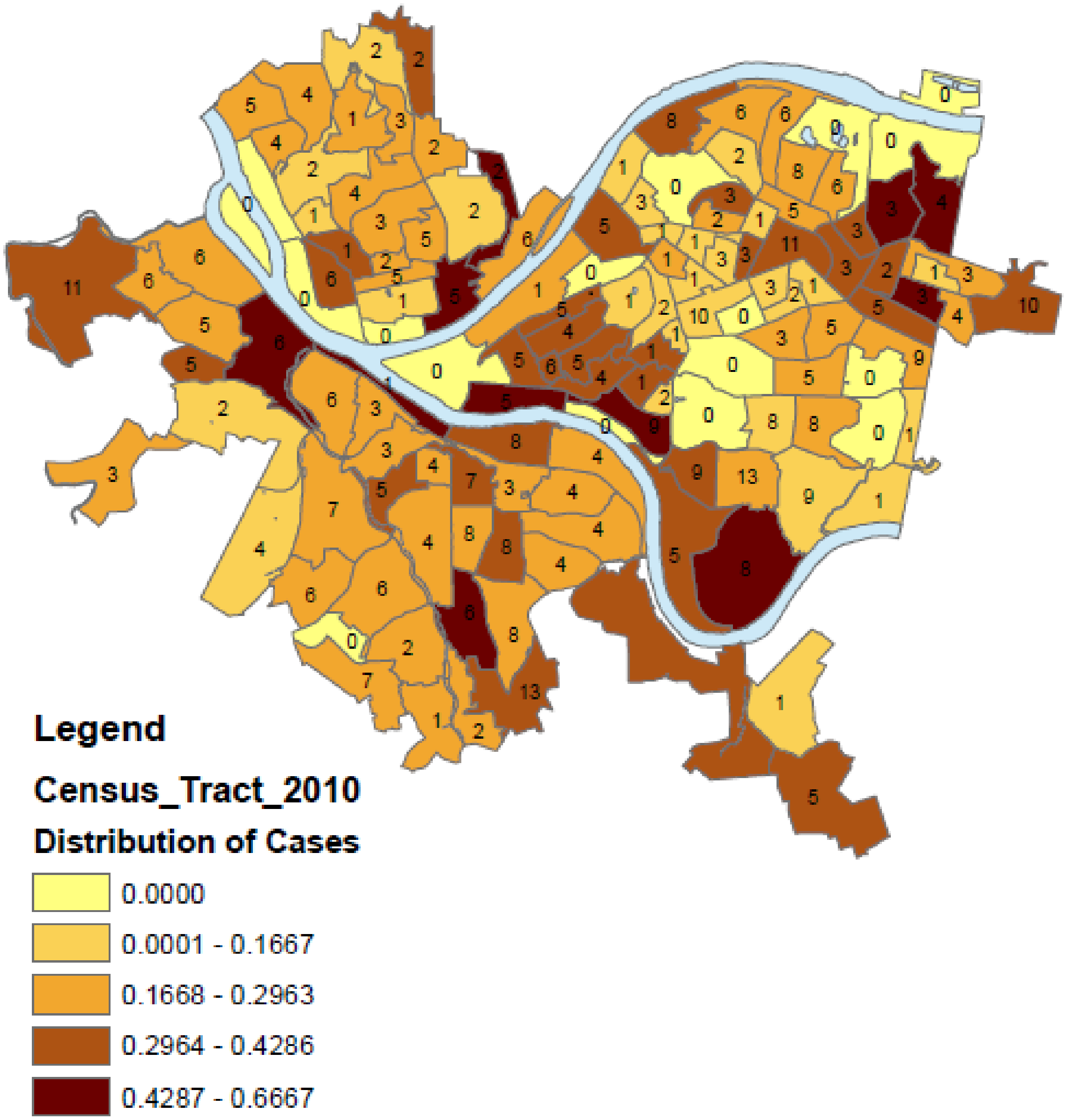


Figure 8A: Case Distributions

APPENDIX B: SUPPLEMENTAL TABLES

Table 8B: Race Model Synthesis

Model	*Point Estimate*	*L95*	*U95*	*-2 Res Log Pseudo-Likelihood*
Race	**1.852**	**1.494**	**2.295**	**8578.37**
Race+Age	1.982	1.54	2.552	8587.58
Race+Marital	1.624	1.262	2.089	8586.04
Race+Insurance	1.683	1.33	2.13	8582.83
Race+Percent Greenery	1.807	1.448	2.256	8103.59
Race+Crime	1.81	1.432	2.288	8230.86
Race+PS	1.751	1.376	2.229	8570.25
Race+MHI	1.677	1.307	2.15	8278.47
Race+SNAP	1.685	1.306	2.17	8551.19
Race+Unemployment	1.776	1.398	2.257	8323.04
Race+MHI Change	**1.865**	**1.467**	**2.369**	**7420.24**
Race+Unemployment Change	1.78	1.408	2.25	7501.37
Race+Pop Change	1.963	1.518	2.537	7689.76
Race+MHI Change+Percent Greenery	**1.79**	**1.396**	**2.296**	**6988.72**
Race+MHI Change+Crime	1.836	1.415	2.383	7235.97
Race+MHI Change+PS	1.68	1.287	2.195	7430.73
Race+MHI Change+MHI	1.686	1.283	2.216	7434.52
Race+MHI Change+SNAP	1.665	1.256	2.208	7430.63
Race+MHI Change+Unemployment	1.697	1.307	2.203	7432.6
Race+MHI Change+Unemployment Change	1.845	1.45	2.347	7427.21
Race+MHI Change+Pop Change	1.945	1.497	2.528	7426.82

Table 8B Continued

Model	*Point Estimate*	*L95*	*U95*	*-2 Res Log Pseudo-Likelihood*
Race+MHI Change+Percent Greenery+Crime	**1.794**	**1.373**	**2.342**	**6848.93**
Race+MHI Change+Percent Greenery+PS	1.639	1.246	2.156	6997.89
Race+MHI Change+Percent Greenery+MHI	1.652	1.245	2.19	7001.95
Race+MHI Change+Percent Greenery+SNAP	1.632	1.223	2.178	6999.12
Race+MHI Change+Percent Greenery+Unemployment	1.616	1.234	2.117	7001.11
Race+MHI Change+Percent Greenery+Unemployment Change	1.772	1.38	2.276	6994.73
Race+MHI Change+Percent Greenery+Pop Change	1.898	1.445	2.493	6995.01
Race+MHI Change+Percent Greenery+Crime+PS	1.689	1.274	2.24	6857.26
Race+MHI Change+Percent Greenery+Crime+MHI	1.696	1.273	2.259	6860.53
Race+MHI Change+Percent Greenery+Crime+SNAP	1.67	1.245	2.241	6860.17
Race+MHI Change+Percent Greenery+Crime+Unemployment	1.644	1.243	2.173	6861.98
Race+MHI Change+Percent Greenery+Crime+Unemployment Change	1.777	1.36	2.322	6854.5
Race+MHI Change+Percent Greenery+Crime+Pop Change	1.868	1.412	2.472	6853.41
Race+MHI Change+Percent Greenery+Crime+Age	1.802	1.34	2.424	6855.8
Race+MHI Change+Percent Greenery+Crime+Marital	1.562	1.161	2.102	6858.85
Race+MHI Change+Percent Greenery+Crime+Insurance	1.662	1.254	2.202	6851.65
Race+MHI Change+Percent Greenery+Crime	***1.794***	***1.373***	***2.342***	***6848.93***
Race+MHI Change+Percent Greenery+Crime+BMI	***1.685***	***1.285***	***2.21***	***6874.37***

Table 9B: Neighborhood Correlation Matrix

	Unemployment	*SNAP*	*Below Poverty*
Median Household Income	-0.54 <.0001	-0.67 <.0001	-0.75 <.0001
Unemployment	-	0.62	0.41
	-	<.0001	<.0001
SNAP	-	-	0.57
	-	-	<.0001

Table 10B: SNAP Model Synthesis

Model	*Point Estimate*	*L95*	*U95*	*-2 Res Log Pseudo-Likelihood*
SNAP	**2.061**	**1.529**	**2.777**	**10259.82**
SNAP+Percent Greenery	2.105	1.528	2.9	9474.44
SNAP+Crime	1.833	1.294	2.596	9830.42
SNAP+Pop Change	2.205	1.554	3.13	9279.82
SNAP+MHI Change	**2.026**	**1.462**	**2.807**	**8941.16**
SNAP+Unemployment Change	1.867	1.349	2.583	9072.07
SNAP+MHI Change+Crime	1.862	1.279	2.711	8696.28
SNAP+MHI Change+Greenery	**1.933**	**1.349**	**2.77**	**8198.11**
SNAP+MHI Change+Pop Change	2.213	1.529	3.202	8950.42
SNAP+MHI Change+Unemployment Change	1.908	1.361	2.677	8952
SNAP+MHI Change+Greenery+Crime	***1.886***	***1.26***	***2.823***	***8028.46***
SNAP+MHI Change+Greenery+Pop Change	2.215	1.463	3.352	8207.42
SNAP+MHI Change+Greenery+Unemployment Change	1.822	1.254	2.646	8206.29
SNAP+MHI Change+Greenery+Crime+Pop Change	2.069	1.337	3.202	8035.63
SNAP+MHI Change+Greenery+Crime+Unemployment Change	1.801	1.193	2.72	8036.49
SNAP+MHI Change+Greenery+Crime+Race (0 1 2)	**1.363**	**0.865**	**2.149**	**7542.33**
SNAP+MHI Change+Greenery+Crime+Age	1.763	1.155	2.689	8039.16
SNAP+MHI Change+Greenery+Crime+Marital	1.468	0.951	2.264	8047.21
SNAP+MHI Change+Greenery+Crime+Insurance	1.637	1.077	2.487	8038.95
SNAP+MHI Change+Greenery+Crime+Race (0 1 2)+Age	1.376	0.868	2.182	7549.23
SNAP+MHI Change+Greenery+Crime+Race (0 1 2)+Marital	1.221	0.764	1.952	7551.45
SNAP+MHI Change+Greenery+Crime+Race (0 1 2)+Insurance	1.274	0.803	2.023	7543.58
SNAP+MHI Change+Greenery+Crime+Race (0 1 2)	***1.363***	***0.865***	***2.149***	***7542.33***

Table 11B: Poverty Status Synthesis

Model	*Point Estimate*	*L95*	*U95*	*-2 Res Log Pseudo-Likelihood*
PS	**1.636**	**1.239**	**2.162**	**10252.83**
PS+Percent Greenery	1.656	1.252	2.19	9476.17
PS+Crime	1.406	1.024	1.931	9811.64
PS+Pop Change	1.72	1.233	2.397	9260.65
PS+MHI Change	**1.839**	**1.343**	**2.52**	**8927.66**
PS+Unemployment Change	1.643	1.216	2.219	9057.84
PS+MHI Change+Greenery	**1.774**	**1.289**	**2.443**	**8189.7**
PS+MHI Change+Crime	1.619	1.136	2.306	8684.58
PS+MHI Change+Pop Change	1.861	1.306	2.651	8935.71
PS+MHI Change+Unemployment Change	1.75	1.27	2.411	8939.67
PS+MHI Change+Greenery+Crime	***1.644***	***1.149***	***2.351***	***8017.2***
PS+MHI Change+Greenery+Pop Change	1.853	1.297	2.647	8197.44
PS+MHI Change+Greenery+Unemployment Change	1.704	1.229	2.363	8199.19
PS+MHI Change+Greenery+Crime+Pop Change	1.713	1.172	2.504	8024.06
PS+MHI Change+Greenery+Crime+Unemployment Change	1.601	1.117	2.296	8026.38
PS+MHI Change+Greenery+Crime+Race (0 1 2)	**1.379**	**0.934**	**2.036**	**7540.18**
PS+MHI Change+Greenery+Crime+Age	1.546	1.069	2.235	8030.15
PS+MHI Change+Greenery+Crime+Marital Status	1.38	0.952	1.998	8047.96
PS+MHI Change+Greenery+Crime+Insurance	1.456	1.008	2.104	8035.58
PS+MHI Change+Greenery+Crime+Race (0 1 2)+Age	1.387	0.936	2.054	7547.07
PS+MHI Change+Greenery+Crime+Race (0 1 2)+Marital Status	1.278	0.861	1.897	7553.35
PS+MHI Change+Greenery+Crime+Race (0 1 2)+Insurance	1.31	0.883	1.942	7544.66
PS+MHI Change+Greenery+Crime+Race (0 1 2)	***1.379***	***0.934***	***2.036***	***7540.18***

Table 12B: Unemployment Model Synthesis

Model	*Point Estimate*	*L95*	*U95*	*-2 Res Log Pseudo-Likelihood*
Unemployment	**1.712**	**1.276**	**2.297**	**10012.89**
Unemploy+Percent Greenery	1.781	1.319	2.406	9234.27
Unemploy+Crime	1.571	1.131	2.184	9599.02
Unemploy+Pop Change	1.946	1.356	2.791	9143.75
Unemploy+MHI Change	**1.866**	**1.352**	**2.576**	**8931.74**
Unemploy+Unemployment Change	1.81	1.311	2.497	9070.3
Unemploy+MHI Change+Percent Greenery	**1.957**	**1.403**	**2.729**	**8197.89**
Unemploy+MHI Change+Crime	1.752	1.222	2.513	8691.41
Unemploy+MHI Change+Pop Change	2.002	1.381	2.903	8939.27
Unemploy+MHI Change+Unemployment Change	1.826	1.306	2.553	8947.84
Unemploy+MHI Change+Percent Greenery+Crime	***1.984***	***1.368***	***2.876***	***8030.05***
Unemploy+MHI Change+Percent Greenery+Pop Change	2.227	1.5	3.306	8205.85
Unemploy+MHI Change+Percent Greenery+Unemployment Change	1.917	1.347	2.728	8206.69
Unemploy+MHI Change+Percent Greenery+Crime+Pop Change	2.26	1.481	3.448	8037.67
Unemploy+MHI Change+Percent Greenery+Crime+Unemployment Change	1.969	1.329	2.917	8037.83
Unemploy+MHI Change+Percent Greenery+Crime+Race (0 1 2)	**1.621**	**1.087**	**2.418**	**7545.69**
Unemploy+MHI Change+Percent Greenery+Crime+Age	1.881	1.284	2.756	8042.24
Unemploy+MHI Change+Percent Greenery+Crime+Marital	1.671	1.136	2.458	8053.45
Unemploy+MHI Change+Percent Greenery+Crime+Insurance	1.772	1.211	2.592	8043.76
Unemploy+MHI Change+Percent Greenery+Crime+Race (0 1 2)+Age	1.641	1.095	2.459	7552.2
Unemploy+MHI Change+Percent Greenery+Crime+Race (0 1 2)+Marital	1.503	1.001	2.257	7557.22
Unemploy+MHI Change+Percent Greenery+Crime+Race (0 1 2)+Insurance	1.538	1.025	2.305	7548.16
Unemploy+MHI Change+Percent Greenery+Crime+Race (0 1 2)	***1.621***	***1.087***	***2.418***	***7545.69***

Table 13B: Median Household Income Model Synthesis

Model	*Point Estimate*	*L95*	*U95*	*-2 Res Log Pseudo-Likelihood*
MHI	**0.53**	**0.40**	**0.70**	**9909.6**
MHI+Percent Greenery	0.50	0.38	0.68	9126.11
MHI+Crime	0.59	0.42	0.82	9665.57
MHI+Pop Change	**0.50**	**0.35**	**0.71**	**8926.94**
MHI+MHI Change	0.48	0.35	0.68	8937.63
MHI+Unemployment Change	0.57	0.42	0.77	8928.66
MHI+Pop Change+Percent Greenery	**0.48**	**0.33**	**0.69**	**8192.89**
MHI+Pop Change+Crime	0.57	0.39	0.83	8683.07
MHI+Pop Change+MHI Change	0.44	0.30	0.65	8945.09
MHI+Pop Change+Unemployment Change	0.54	0.38	0.78	8937.14
MHI+Pop Change+Percent Greenery+Crime	***0.51***	***0.34***	***0.77***	***8020.04***
MHI+Pop Change+Percent Greenery+MHI Change	0.44	0.29	0.66	8203.57
MHI+Pop Change+Percent Greenery+Unemployment Change	0.49	0.33	0.73	8200.3
MHI+Pop Change+Percent Greenery+Crime+MHI Change	0.46	0.29	0.72	8030.28
MHI+Pop Change+Percent Greenery+Crime+Unemployment Change	0.52	0.34	0.80	8026.9
MHI+Pop Change+Percent Greenery+Crime+Race (0 1 2)	**0.65**	**0.42**	**1.02**	**7537.24**
MHI+Pop Change+Percent Greenery+Crime+Age	0.55	0.36	0.83	8032.03
MHI+Pop Change+Percent Greenery+Crime+Marital	0.63	0.41	0.97	8039.47
MHI+Pop Change+Percent Greenery+Crime+Insurance	0.59	0.38	0.90	8033.5
MHI+Pop Change+Percent Greenery+Crime+Race (0 1 2)+Age	0.65	0.41	1.02	7543.75
MHI+Pop Change+Percent Greenery+Crime+Race (0 1 2)+Marital	0.71	0.45	1.125	7546.27
MHI+Pop Change+Percent Greenery+Crime+Race (0 1 2)+Insurance	0.69	0.44	1.09	7540.49
MHI+Pop Change+Percent Greenery+Crime+Race (0 1 2)	***1.532***	***0.979***	***2.397***	***7537.24***

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