Integrating Social and Neighborhood Contexts to Understand Low Birthweight Inequalities

by

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DISSERTATION ABSTRACT

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This dissertation explores the ways in which social and spatial contexts interact to affect the patterning of low birthweight (LBW) inequalities. I utilize a fundamental causes perspective and ecosocial theory to look at how race/ethnicity and socioeconomic status operate as social determinants of low birthweight at multiple levels. To address these research aims, I complete three empirical analyses. First, I conduct a neighborhood level spatial analysis to look at the relationships between racial/ethnic composition, family structure, neighborhood deprivation, and LBW rates across California census tracts. Findings show that LBW rates are patterned by racial/ethnic composition, percent female headed households and neighborhood deprivation. However, these relationships are not uniform across racial/ethnic composition groups. Next, I build on this with a multilevel analysis of nationally representative Add Health data on births to look at the relationship between race/ethnicity and LBW at the individual level and the neighborhood level separately, additively, and interactively. Black racial identity and higher Black neighborhood composition are both associated with higher risk of LBW, but the compositional effect appears to be driven by an accumulation of individual effects. Further, Black mothers appear to experience a protective effect from living in higher percent Black neighborhoods. Finally, I again use Add Health birth data and I employ innovative intersectional multilevel models to look at the intersectional patterning of LBW by race/ethnicity and socioeconomic status and consider how the effect of neighborhood median household income on LBW varies across intersectional groups. Results indicate that there is considerable inequality in

the risk of LBW across intersectional groups. Further, the effect of median household income on LBW risk varies across these groups. Taken as a whole, the findings in this dissertation demonstrate that low birthweight inequalities are patterned by race/ethnicity and socioeconomic status at both the individual and the neighborhood level. Black mothers and communities experience particularly high risk of LBW. Further, neighborhood contextual effects vary for individuals from different social groups. These findings highlight the importance of multilevel thinking when looking at health inequalities and highlight the need for programs and policies that support high risk mothers, infants, and communities.

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DEDICATION

I dedicate this dissertation to all my family and friends who have supported my graduate school endeavors.

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CHAPTER I

INTRODUCTION

Health inequalities are shaped by social determinants, such as sexism, racism, and classism. Studying health inequalities can reveal broader patterns of inequalities in society and can provide a better understanding of how inequalities are patterned and produced which can lead to improved and more equitable outcomes.

Low birthweight is an important health metric that is useful for looking at the patterning of health inequalities because it is reflective of social determinants that affect mothers' health such as maternal race/ethnicity (Alhusen et al. 2016; Almeida et al. 2018; Choi and Martinson 2018; Geronimus 1996; Lu and Halfon 2003) and socioeconomic status (Blumenshine et al. 2010; Finch 2003; Jansen et al. 2008; Ncube et al. 2016; Ramraj et al. 2020). Further, low birthweight is associated with lower socioeconomic attainment later in life (Bilgin, Mendonca, and Wolke 2018), suggesting that it may be one way that intergenerational transmission of disadvantage occurs.

In this dissertation, I examine low birthweight inequalities as I aim to contribute to a more complete understanding of how social and spatial contexts interact to influence health inequalities. In this chapter, I provide a summary of the relevant literature and existing research, discuss remaining gaps in health inequalities and low birthweight research, and provide an overview of my empirical analyses. In the following three chapters I present the results of three empirical studies that explore the patterning of LBW inequalities. In the final chapter I summarize the results of my analyses and discuss key takeaways and directions for future research.

Social Determinants of Health Inequalities

Social conditions directly affect health and can lead to health inequalities that reflect broader patterns of social inequalities. In his foundational work, Frederick Engels (2005) looked at the relationship between social class and health in England in the mid-nineteenth century and found striking health inequalities between the lower and upper classes. He determined that these inequalities were due to social conditions, not individual characteristics, and he detailed horrific living conditions in which working class individuals and families were subject to overcrowding, pollution, famine, insufficient clothing, poor quantity and quality of food, and insufficient medical care. He noted that these conditions lead to premature death, high rates of disease, and states of hopelessness and demoralization. This work was highly influential in demonstrating that poor health outcomes were not caused by individual factors, but rather social conditions associated with economic class.

More recently, an influential study by Marmot, Shipley, and Rose (1984) looked at the relationship between employment grade and health in London using data from the Whitehall study of civil servants. Results from this study, which looked at mortality in men who were working in office-based civil servant jobs in London over a ten-year period, showed a clear mortality gradient for several causes of death, with the rate of death increasing as employment grade decreased. This gradient was partially explained by risk factors such as smoking, physical activity, and blood pressure. However these did not fully explain differences in mortality.

Link and Phelan (1995) argued that social determinants, such as sexism, racism, and classism, operate as fundamental causes of health inequalities by influencing exposure to risk factors that can affect health and by affecting access to resources to minimize the effects of disease if it does occur. They contended that individually based risk factors or disease must be contextualized within fundamental causes, or risks of risk, such as socioeconomic status and social support. They note that fundamental causes of disease involve access to resources, operating through multiple mechanisms to affect multiple disease outcomes, and therefore continue to be associated with disease even when proximal mechanisms change. They argue that failure to acknowledge the role of fundamental causes may result in ineffective intervention strategies. Link and Phelan specifically identify socioeconomic status (SES) as a fundamental cause of disease. They note that over time, even as SES inequalities in some diseases have disappeared due to advancements in sanitation and immunization, SES inequalities in other diseases have emerged. This is in part because as new health risks and conditions emerge, higher SES individuals have better access to information and resources that help them avoid risks of disease and minimize negative outcomes of disease when it does occur.

Race and racism are also important social determinants of health. In the U.S., structural racism affects health in many ways through mutually reinforcing systems that are historically rooted and culturally reinforced (Bailey et al. 2017). In his seminal work in the early twentieth century, W.E.B. Du Bois detailed the harms and challenges faced by Black individuals following the Civil War (Du Bois 2003). This work was influential in highlighting the material effects of race and racism in the U.S. More recently, scholars have argued that race is a social construction, and racial identities are determined by social, economic, and political forces. Race is used as a means of control in which minority groups are limited in their freedom, upward mobility, economic gain, and social expectations (Omi and Winant 2014). Further, racism is embedded in our social structures and continues to be perpetuated even without anyone explicitly intending to perpetuate it or the presence of overt racism (Bonilla-Silva 2021; Omi and Winant 2014). Institutional racism such as drug policies that disproportionately target Black people for incarceration and discrimination in rental and housing markets against Black and Latino communities are rooted in historical policies and practices, but remain pervasive and continue to have adverse physical, social, and economic effects that are harmful to health (Bailey et al. 2017).

Racism has been identified as a fundamental cause of health inequalities. Phelan and Link (2015) note that racism operates as a fundamental cause of health inequalities in part because race and SES are closely connected in the United States. They argue that racism leads to differences in SES which then operates as a fundamental cause of disease resulting in racial health inequalities. However, they note that there is evidence that racism also operates as a fundamental cause of health inequalities independently of SES through factors such as unequal power, prestige, freedom, neighborhood context, and healthcare.

Krieger's ecosocial theory (Krieger 2001, 2011) complements a fundamental causes perspective in several ways. Krieger similarly argues that it is not sufficient to focus on biological and individual explanations when seeking to understand health inequalities. Instead, we must consider how social environments interact with biology to affect health outcomes. She argues that the material and social world in which we live becomes biologically incorporated, or embodied, throughout our lives. This embodiment occurs at multiple levels and through many pathways, including economic and social deprivation, toxic substances and hazardous conditions, socially inflicted trauma, and inadequate health care. Gravlee (2009) also describes the process of embodiment, detailing how racial inequality becomes embodied in the biology of minority racial groups, leading to racial inequalities in health.

Intersectionality

While much research on health inequalities focuses on the effects of social determinants independently, it is also important to consider how social contexts interact to create unique outcomes. An intersectional framework focuses on the interaction of social identities and is useful when analyzing health inequalities. Intersectionality focuses on interlocking systems of privilege and oppression (Collins 1990; Crenshaw 1990) which can help us understand how inequalities are a result of intersecting social identities rather than separate axes of marginalization. Recently there has been a trend for research on the social production of health inequalities to explicitly use an intersectional framework (Bauer 2014; Bowleg 2012; Evans, Williams, Onnela, and S.V. Subramanian 2018; Evans and Erickson 2019; Merlo 2018).

McCall (2005) identified three approaches to intersectional research: the *anticategorical* approach that aims to deconstruct analytical categories, the *intracategorical* approach that critically recognizes social categories and focuses on particular marginalized social groups, and the *intercategorical* approach that utilizes existing categories to look at patterns of inequality across multiple, intersecting social dimensions such as socioeconomic status, race, and sex. Intersectional research looking at health inequalities often uses the *intracategorical* approach by utilizing qualitative methods to get an in-depth understanding on processes that lead to health inequalities for one particular group. This type of research is important and provides a thorough understanding of inequalities that would be difficult to achieve with other approaches. However, it is also important to look at how different intersectional social groups compare to one another in order to understand the unique ways that different groups experience inequality. This is where an *intercategorical* approach is useful.

Recent methodological advancements have addressed several of the practical and theoretical limitations of prior quantitative intersectional research. Using these novel techniques, recent quantitative intercategorical research has looked at a variety of health related outcomes including depression (Evans and Erickson 2019), cigarette use (Evans 2019b), lead exposure (Liévanos, Evans, and Light 2021), cancer risk from air toxics (Alvarez and Evans 2021), and low birthweight (Evans et al. 2023; Nieves et al. 2023).

Neighborhoods and Health

Returning to fundamental causes, Williams and Collins (2001) identify racial residential segregation as a fundamental cause of racial disparities in health. They note that this in part occurs through processes related to SES such as differential access to education and employment opportunities. However, they argue that segregation also leads to racial differences independently of SES by leading to social and physical conditions that are harmful to health. Gee and Payne-Sturges (2004) argued that living in disadvantaged communities increases exposure to environmental hazards which may increase psychosocial stress and lead, directly and indirectly, to health problems. They argued that this may help explain racial and ethnic health disparities.

Liévanos (2019b) looked at the relationship between neighborhood racial composition, concentrated disadvantage, and air pollution in California and found that percent Latinx, percent non-Latinx Black, and percent non-Latinx Asian were positively correlated with fine particulate matter at the neighborhood level. Arcaya et al. (2012) found evidence that life expectancy is driven by spatial processes and argued that consideration of space and membership in geographically-embedded administrative units can provide valuable insight into area variations in health. It is also important to consider gendered family structure when looking at the spatial concentration of health inequalities (Liévanos et al. 2021). Recent research has argued that family structure is closely tied to class, race, and gender inequalities and is an important mechanism through which these inequalities are reproduced (McLanahan and Percheski 2008).

Krieger's (2001, 2011) third construct of an ecosocial approach is interested in the "cumulative interplay between exposure, susceptibility and resistance" and looks at pathways of embodiment at multiple levels and in multiple domains. Further, the six pathways of embodiment that she describes include socio-spatial determinants including residential and occupational segregation that leads to racial inequalities in economic deprivation and inequalities in risk of exposure to toxic substances, such as air pollution and lead paint.

Further, intersectional scholars have focused on the importance of considering the role of contextual processes in producing intersectionally patterned experiences and outcomes (Choo and Ferree 2010; Crenshaw 1990; May 2015). However, intersectional work has often lacked sufficient attention to the role of neighborhood and community context in producing health inequalities. Recent advancements in quantitative intersectional analysis have been used to incorporate neighborhood and community context into research on intersectional health inequalities (Evans 2019b; Evans et al. 2023) and to look at the intersectional patterning of health outcomes at the neighborhood level (Alvarez and Evans 2021)

Low Birthweight Inequalities

Low birthweight (LBW) is an important biomarker of infant health. LBW infants are more often small because they are born early, but they can also be born small at full term due to growth restriction during pregnancy. Births are considered LBW when the baby weighs less than 2,500 grams (about 5.5 pounds). LBW is a useful measure for looking at how health inequalities are patterned and produced because it is an indicator of social determinants that affect mothers' health such as maternal race/ethnicity (Alhusen et al. 2016; Almeida et al. 2018; Choi and

Martinson 2018; Geronimus 1996; Lu and Halfon 2003) and socioeconomic status (Blumenshine et al. 2010; Finch 2003; Jansen et al. 2008; Ncube et al. 2016; Ramraj et al. 2020). LBW is a predictor of higher risk of infant mortality (Ely and Driscoll 2021; Pusdekar et al. 2020) and several health and developmental outcomes in childhood and adulthood including asthma, hypertension, and diabetes (Barker et al. 2002; Choi and Martinson 2018; Hassan et al. 2021; Nepomnyaschy and Reichman 2006; Whincup et al. 2018). Further, LBW is linked to an increased sensitivity to environmental exposures such as air pollution (Faust et al. 2017) and is associated with lower socioeconomic attainment later in life (Bilgin et al. 2018), suggesting that is may be one way that intergenerational transmission of disadvantage occurs.

Stress is an important mechanism through which social determinants become embodied and affect LBW risk (Turner 2010; Wadhwa et al. 2011). Geronimus (1996) describes a "weathering" effect where exposure to discrimination, environmental hazards, and other stressors among racially/ethnically minoritized mothers causes an increased risk of LBW. The weathering hypothesis suggests that racially/ethnically minoritized individuals experience excess chronic activation of psychosocial stress pathways that lead to the embodiment of these experiences in the form of premature biological aging (Geronimus et al. 2006). In a key study, Geronimus (1996) found that Black women, particularly those residing in low-income areas, experience accelerated aging, in part due to stress, that causes an increased risk of having a LBW baby compared to white mothers. Not only is the risk of LBW for Black mothers higher than for white mothers at all ages, the relationship between age and LBW risk is shaped differently for these two groups. While white women generally experience a J-shaped relationship between age and LBW risk, with a decrease in risk from the teenage years into the late twenties and then an increase in risk after that, Black women start with a higher risk of LBW than white women in their teen years that increases at an increased rate with age so that by their early thirties, Black women have a substantially higher risk of LBW than white women.

The importance of the role of stress in the relationship between race/ethnicity and LBW risk is further supported by Lu and Halfon's (2003) review of studies on racial and ethnic disparities in birth outcomes. They note that poor birth outcomes, including LBW, are disproportionately high among Black women compared to Hispanic and non-Hispanic white women and they propose that these disparities in birth outcomes result from differences in developmental trajectories that start with early life experiences and differences in cumulative allostatic load over the life course. Geronimus et al. (2006) note that allostatic load is "the cumulative wear and tear on the body's systems owing to repeated adaptation to stressors" and find that Black individuals on average have higher allostatic load scores at all ages than white individuals.

The relationship between risk of LBW and other racial/ethnic identities is less clear, perhaps because categories such as "Asian" and "Hispanic" encompass several diverse subgroups. One such distinction within these categories that may play a role in birth outcomes is nativity or immigration status. On the one hand, being foreign-born could result in poor birth outcomes due to social, political, economic, and legal vulnerability, particularly among asylum seekers and refugees (Heslehurst et al. 2018). However, research has sometimes shown a "healthy immigrant' effect in which immigrants experience better health outcomes than their non-immigrant counterparts and in which health outcomes worsen the longer immigrants reside in the U.S., possibly due to differential exposure to U.S. racial hierarchies and acculturation (Andrasfay and Goldman 2020; Ghazal Read and Emerson 2005). These patterns are also observed in research on birth outcomes, including birthweight (Acevedo-Garcia, Soobader, and Berkman 2007; Andrasfay and Goldman 2020; Heslehurst et al. 2018).

Further, research has shown a link between SES and LBW, with higher rates of LBW among women with less education (Jansen et al. 2008) and with lower household incomes (Finch 2003). Koning and Ehrenthal (2019) identified "stressor landscapes" that consist of differing patterns of stressful maternal life events preceding birth. They found that low income and minority women are at greater risk of experiencing preterm birth and LBW, in part because they are more likely to experience toxic stressor landscapes.

An intersectional framework is useful when looking at inequalities in LBW and other birth outcomes. An *intracategorical* approach can provide insight into the experiences of particular marginalized groups within broader groups in which they belong. For instance, a recent study investigated Black pregnant women's experiences of gendered racism during pregnancy (Mehra et al. 2020). An *intercategorical* approach can reveal patterns of inequality across multiple, intersecting social dimensions. Recent research demonstrated that birthweight inequalities in New York City are patterned by intersectional social strata consisting of intersecting social identities (Nieves et al. 2023) and found evidence of intersectional inequalities in birthweight outcomes for twin and singleton births (Evans et al. 2023).

Like health inequalities generally, it is useful to consider neighborhood context when looking at LBW. LBW inequalities in the U.S. have been shown to be geographically concentrated, with disproportionately high rates in Black and low-income communities (Liévanos 2019b; Morenoff 2003). Many of the mechanisms that influence LBW, such as pollution and access to healthcare, occur at the neighborhood or community level. For instance, Shi (2004) found that having more primary care providers in an area was associated with better birthweight outcomes, especially in areas with high levels of social disparities. Further, Rich et al. (2015) looked at low birthweight rates among babies born to women in Beijing who were pregnant during the 2008 Olympics, which was a time when air pollution was significantly lower than normal. They found that babies whose 8th month of gestation occurred during the 2008 Olympics were on average 23 grams larger than babies whose 8th month of gestation occurred during the same calendar dates the year before or the year after.

According to Morenoff (2003), socio spatial determinants of LBW include stress and adaptation mechanisms that occur through conditions created by structural factors like concentrated disadvantage. Findings specifically identified that prolonged exposure to violent crime is associated with greater risk of LBW, while neighborhood social relationships and engagement provide a protective effect that decreases the risk of LBW. Further, prior research has shown that residential segregation is linked to adverse birth outcomes (Mehra, Boyd, and Ickovics 2017). Krieger et al. (2020) found evidence that historical redlining in New York City may be a determinant of present-day preterm birth risk and De Maio et al. (2017) found racial/ethnic segregation to be significantly associated with LBW in Chicago.

Empirical Approach

Despite the abundance of research on LBW inequalities, there are still a few important gaps in the existing literature. Neighborhood-level studies of LBW inequalities often focus on a small area, such as a single city or county (Campbell et al. 2018; Legerski and Thayn 2013; Morenoff 2003; Schulz et al. 2020) and few studies have looked at these patterns across a wide and diverse area. Further, few studies have simultaneously considered multiple neighborhood context variables such as racial/ethnic composition, family structure, and neighborhood deprivation in the patterning of LBW rates.

Importantly, inequalities in LBW have often been studied at the individual *or* the neighborhood level. However, it is useful to consider both levels simultaneously, as LBW is shaped by factors that occur at the individual level and the neighborhood level. Subramanian et al. (2009) revisited the famous 1950 article by Robinson (1950) that led to awareness and warnings about ecological fallacy. Subramanian et al. demonstrated that there are perils presented by ecological fallacy, but that there are also perils posed by individualistic fallacy. They argued that historically informed multilevel thinking is a necessity.

In the following chapters, I address these gaps and build on the existing literature with three empirical analyses that contribute to a better understanding of how LBW inequalities are patterned and produced. In Chapter 2, I complete a neighborhood-level spatial analysis to look at the relationship between racial/ethnic composition and LBW rates across California census tracts. I also consider the role of family structure and neighborhood deprivation in this relationship. Chapters 3 uses nationally representative data to build on this by considering the role of individual-level race/ethnicity and neighborhood-level racial/ethnic composition simultaneously. I conduct a multilevel analysis to look at how race/ethnicity at both levels shape LBW risk separately, additively, and interactively. I consider the extent to which racial/ethnic disparities are driven by individual-level race/ethnicity and the extent to which they are driven by neighborhood-level racial/ethnic composition. I then consider whether living in a neighborhood with a high percentage of the population belonging to one's own racial/ethnic group provides a protective effect for risk of LBW. In Chapter 4, I use nationally representative data to further consider how LBW risk is shaped at multiple levels by employing an intersectional framework and innovative intersectional multilevel models to look at how LBW inequalities are patterned intersectionally. I start by looking at LBW risk across intersectional social strata that consist of race/ethnicity and SES. I then consider how the effect of census tract-level median household income on LBW varies across intersectional social strata.

CHAPTER II

A SPATIAL ANALYSIS OF RACIAL/ETHNIC COMPOSTION AND LOW BIRTHWEIGHT RATES ACROSS CALIFORNIA CENSUS TRACTS

Introduction

Low birthweight (LBW) is an important biomarker of infant health. It is associated with a higher risk of infant mortality (Ely and Driscoll 2021; Pusdekar et al. 2020) and several health and developmental outcomes later in life, including asthma, hypertension, and diabetes (Barker et al. 2002; Choi and Martinson 2018; Hassan et al. 2021; Nepomnyaschy and Reichman 2006; Whincup et al. 2018). LBW is also an indicator of social determinants, which function as "fundamental causes" of health inequalities through systemic racism, sexism, and classism by affecting access to resources including economic resources, social supports, and quality healthcare (Link and Phelan 1995; Phelan and Link 2015). Social determinants of LBW and that affect mothers' health include a variety of social sources of stress (Geronimus 1996; Koning and Ehrenthal 2019), maternal race/ethnicity (Alhusen et al. 2016; Almeida et al. 2018; Choi and Martinson 2018; Geronimus 1996; Lu and Halfon 2003), and maternal socioeconomic status (Blumenshine et al. 2010; Finch 2003; Jansen et al. 2008; Ncube et al. 2016; Ramraj et al. 2020). Further, LBW is associated with lower socioeconomic attainment later in life (Bilgin et al. 2018), suggesting that it may be one process through which intergenerational transmission of disadvantage occurs. Although there is an abundance of research on the patterning of LBW inequalities at the individual level, it is also important to understand how inequalities in neighborhood-level LBW rates are patterned as many mechanisms that influence LBW occur at the neighborhood or community level, such as air pollution (Rich et al. 2015) and access to healthcare (Shi 2004).

LBW inequalities in the U.S. have been shown to be geographically concentrated, with disproportionately high rates in Black and low-income communities (Liévanos 2019b; Morenoff 2003). However, much is still unknown about how these inequalities are patterned and the mechanisms that drive them. Much of the existing research at the neighborhood level focuses on a small area such as a single city or county (Campbell et al. 2018; Legerski and Thayn 2013; Morenoff 2003; Schulz et al. 2020). Further, few studies have simultaneously considered the role of racial/ethnic composition, family structure, and neighborhood deprivation in the patterning of LBW rates. Higher rates of LBW among already marginalized communities add an additional burden that further disadvantages these communities. Understanding how and why certain communities experience higher LBW rates can aid in policy and other interventions aimed at supporting equitable health outcomes.

To address these gaps in the literature and inform health equity policy, I conduct a spatial analysis of the relationship between racial/ethnic composition and LBW rates at the census tract level across California. I then consider how family structure, specifically the extent of female-headed households (FHH), and neighborhood deprivation affect this relationship. Findings show that percent Black, percent Hispanic, percent Asian, and percent Native are all positively associated with LBW rates, but the strength of the relationship varies across racial/ethnic groups. Further, percent FHH and neighborhood deprivation appear to account for some of this relationship, but this effect is not uniform.

Literature Review

Stress is an important mechanism through which social determinants affect LBW (Turner 2010; Wadhwa et al. 2011). Geronimus (1996) concluded that Black women have worse LBW outcomes than white women in part due to premature biological "weathering" that is caused by stress from experiences of sexism and racism. Additionally, Koning and Ehrenthal (2019) find that risk of preterm birth and LBW is higher among low-income and racial minority women in part due to their higher likelihood of experiencing "stressor landscapes."

While studies on LBW inequalities often focus on individual-level social determinants, many factors that influence LBW occur at the neighborhood or community level such as exposure to hazardous environments (Rich et al. 2015) and access to quality healthcare (Shi 2004). Krieger's (2001, 2011) ecosocial theory posits that our health is affected when the material and social world in which we live becomes embodied which leads to health inequalities. Embodiment occurs at multiple ecological levels and includes socio-spatial determinants of health, which play a role in LBW outcomes.

Racist, classist, and gendered processes can lead to community level health inequalities. Research has shown that contextual factors affect LBW risk both directly and indirectly and that racial and ethnic differences in LBW are driven in part by the characteristics of the county where the mother resides (Gorman 1999). Using U.S. birth data from 1990, Gorman (1999) showed that at the county level, the percent of the population that was foreign-born, the percent of families that were female headed, and median household income affected risk of LBW. These effects differed across racial/ethnic groups. Further, LBW inequalities are geographically concentrated in the U.S., with rates particularly elevated in Black and low-income communities (Liévanos 2019b; Morenoff 2003). Such racialized neighborhood-level health inequalities occur through multiple complex processes, particularly through the fundamental cause of residential segregation (Williams and Collins 2001).

As Williams and Collins (2001) elaborate, residential segregation leads to racial differences in SES by affecting access to education and employment opportunities. These differences in SES then lead to racial differences in health. In addition, they note that segregation leads to social and physical conditions that are harmful to health. Prior research has shown that residential segregation is linked to adverse birth outcomes (Mehra et al. 2017). Krieger et al. (2020) found evidence that historical redlining in New York City may be a determinant of present-day preterm birth risk and De Maio et al. (2017) found racial/ethnic segregation to be significantly associated with LBW in Chicago.

Another way that residential segregation may affect risk of LBW is through exposure to environmental hazards. For instance air pollution exposure has been linked to an increased risk of LBW (Rich et al. 2015) and previous research has shown disproportionately high exposures to air pollution among single-mother families (Downey, Crowder, and Kemp 2017; Downey and Hawkins 2008) and minoritized racial/ethnic households (Crowder and Downey 2010). Liévanos, Evans, and Light (2021) found that among neighborhood-level indicators of racialized single-parent families, elevated percentages of single-father Black and single-mother Latina families were associated with significantly higher likelihood of census block exposure to lead water service lines during the Flint Water Crisis. They attribute those findings to how family structure is closely tied to class, race, and gender inequalities within education, housing, and labor markets and is an important mechanism through which these inequalities are reproduced in the United States (Ducre 2018; Highsmith 2015; Howard 2013; McLanahan and Percheski 2008)

Additional socio-spatial determinants of LBW include stress and adaptation mechanisms that occur though conditions created by structural factors like concentrated disadvantage that is disproportionately experienced by Black and Latinx communities (Morenoff 2003). In the case of Chicago, Morenoff (2003) found that prolonged exposure to violent crime is associated with greater risk of LBW. Further, neighborhood social relationships and engagement provide a protective effect that decreases the risk of LBW.

Despite previous work that has considered neighborhood-level LBW inequalities, much of the existing research at the neighborhood level focuses on a small area such as a single city or county (Campbell et al. 2018; Legerski and Thayn 2013; Morenoff 2003; Schulz et al. 2020) and few studies have looked at these patterns across a wide and diverse area. Further, few studies have simultaneously considered the role of racial/ethnic composition, family structure, and neighborhood deprivation in the patterning of LBW rates.

Research Aims

To address these gaps and add to the understanding of how inequalities in neighborhood-level LBW rates are patterned, I analyze California census tract data with spatial lag regression models. The objectives of the analysis are twofold: evaluate the relationships between racial/ethnic composition and LBW rate and consider the effect of census tract-level percent of female-headed households and neighborhood deprivation on these relationships.

Specifically, I consider the effect of non-Hispanic Black, Hispanic, non-Hispanic Asian, and non-Hispanic Native composition. Native populations are often omitted from studies looking at health inequalities, frequently due to lack of data availability, but as noted and addressed by recent research (Liévanos 2019a), it is important to consider Indigenous populations in spatial, health-related analyses. Further, a recent review article looked at research on racial/ethnic segregation and health disparities (Yang, Park, and Matthews 2020) and noted the need for more work that looks at segregation between whites and non-Black minorities, especially Hispanics and Asians.

Given the existing literature as well as the structural racism and racial segregation that disproportionately affects Black and Native populations, I expect that higher percent Black composition and higher percent Native composition will be associated with higher LBW rates. Given the heterogeneity with respect to country of origin and immigration status within the Hispanic and Asian racial/ethnic groups, I predict that the strength of the relationships between these compositional groups and LBW rates will be smaller in magnitude. I predict that percent female headed households and neighborhood deprivation will be associated with higher LBW rates. Further, I expect that these variables will somewhat attenuate that relationship between racial/ethnic composition and LBW rates, especially when looking at percent Hispanic and percent Asian composition.

Data and Methods

Data

I utilize data from the California Communities Environmental Health Screening Tool (CalEnviroScreen) and from the 2010 Census. CalEnviroScreen (August et al. 2021) is an environmental justice tool developed by the California Environmental Protection Agency and the Office of Environmental Health Hazard Assessment. This tool contains data on several pollution measures, health outcomes, and demographic variables for all California census tracts. Four versions of CalEnviroScreen have been released to the public since 2013. For this analysis, I am using low birthweight data from the most recent version, CalEviroScreen 4.0, which was released in October 2021, and neighborhood deprivation data from CalEnviroScreen 3.0, which was released in 2017 and updated in June 2018.

In addition to data availability, California is well-suited for this study because its large area and population and its diverse geography and people provide a large study site that encompasses a wide range of social, community, and environmental contexts. Further, recent research has looked at patterns of LBW in California and found disproportionately high rates of LBW among Black women (Enders et al. 2019; Ratnasiri et al. 2018), elevated rates of LBW among Latina women compared to non-Latina whites (Sanchez-Vaznaugh et al. 2016), and high LBW rates concentrated in neighborhoods with a higher proportion of Black residents and lower proportion of Latinx residents (Liévanos 2019b). These studies highlight the importance of further investigation into the patterning of LBW in the state of California.

The *low birthweight* variable in CalEnviroScreen 4.0 is a measure of the percent of births that were considered low birthweight (less than 2,500 grams) for each census tract. This value is an average of low birthweight rates from 2009-2015 as reported by the California Department of Public Health. Births were geocoded based on the mother's residential address at the time of the birth and were excluded if they could not be geocoded. Census tracts with fewer than 50 live births during the data range were considered unreliable estimates and were excluded from the CalEnviroScreen data.

Data on *racial/ethnic composition* and *female headed households* comes from the 2010 Census, acquired from IPUMS NHGIS (Manson et al. 2023). Each racial/ethnic composition variable is the percent of all individuals in each census tract that identify as that race/ethnicity. I utilize four racial ethnic categories for my analysis—*percent non-Hispanic Black*, *percent Hispanic*, *percent non-Hispanic Asian*, and *percent non-Hispanic Native* (hereafter percent

Black, percent Hispanic, percent Asian, and percent Native). I exclude percent non-Hispanic white and percent non-Hispanic other to avoid issues of multicollinearity.

Female headed households is the percent of all households in each census tract that are classified as female headed family households. According to the 2010 U.S. decennial census, "a family consists of a householder and one or more other people living in the same household who are related to the householder by birth, marriage, or adoption. All people in a household who are related to the householder are regarded as members of his or her family" (U.S. Census Bureau 2012:640).

Neighborhood deprivation variables come from CalEviroScreen 3.0. I utilize data from this wave rather than the most recent wave because the dates of data collection for these variables in version 3.0 more closely align with the dates for the LBW variable in version 4.0. Prior work has utilized neighborhood deprivation and racial/ethnic composition variables from CalEnviroScreen to explore how concentrated racialized deprivation affects exposure to pollution (Liévanos 2018, 2019b). To deal with the high correlation between these variables and therefore avoid issues of multicollinearity, this research utilized principal component factor analysis to create factor variables that were used in spatial regression analysis. I utilized a similar, but distinct approach in which I constructed a summated scale that is the standardized sum of four standardized neighborhood deprivation variables: educational attainment, linguistic isolation, poverty, and unemployment. As a sensitivity check, I followed up with a principal component analysis with these four variables. Results indicated that a single component factor had an eigenvalue greater than one (2.78) and that this factor accounted for 69.84% of the variance. This factor variable was almost identical to the summated scale I constructed (r=0.998). I therefore opted to use the deprivation *scale* in the analysis.

Each of the neighborhood deprivation variables used to construct the scale is an average of data from 2011-2015. Educational attainment is the percent of the population over age 25 with less than a high school education, linguistic isolation is the percent of households where all members 14 years old or older have at least some difficulty speaking English, poverty is the percent of the population living below two times the federal poverty level, and unemployment is the percent of the population over the age of 16 that is eligible for the labor force and unemployed. These variables in CalEnviroScreen 3.0 were derived using 2011-2015 American Community Survey (ACS) estimates. CalEnviroScreen 3.0 determined that the ACS estimates were reliable if the standard error was less than half of the estimate or if it was less than the mean standard error for all California census tract estimates. Estimates that did not meet these criteria were not included in the data (Faust 2017).

Analytical Sample

The final analytic sample excludes any tracts missing data for LBW, racial/ethnic composition, percent female headed households, or neighborhood deprivation. Further, five additional tracts were dropped from the analysis due to being neighborless. Neighborless tracts are those that do not share a border with any other tracts due to geography or to being surrounded by tracts that are missing data and therefore cannot be included in the spatial weights matrix used for the spatial regression analysis. The resulting final sample includes 7,619 census tracts.

Methodological Approach

To look at the spatial patterning of racial/ethnic composition and LBW rates, I employ OLS regression and spatial regression models. Spatial regression models use spatial weights matrices to account for spatial dependence (Mitchell 2005; Anselin 2009). This spatial dependence often occurs in spatial data when observations near one another are more similar than observations that are far apart and violates the assumption of traditional OLS regression models that cases are independent of one another. I started by fitting four OLS regression models and calculated Global Moran's I for the residuals with a row-standardized first order queen adjacency matrix. The Moran's I values indicated statistically significant spatial autocorrelation. I then ran Lagrange Multiplier diagnostics which indicated that spatial lag models were appropriate.

The general equation for the spatial lag models is:

$$y = \rho W y + X\beta + \varepsilon$$

where y is a vector of observations of the dependent variables, ρ is a spatial autoregressive parameter, Wy is a spatially lagged weights matrix of the dependent variable, X is a matrix of observations of the explanatory variables, β is a vector of the associated parameter values, and ε is a vector of normally distributed, random error terms. I utilize the same first order queen adjacency matrix that was used to calculate the Moran's I values.

I ran two sets of four models predicting LBW rate—a set of OLS models and a set of spatial lag models. All models were fit in RStudio and spatial lag models were fit using the spatialreg package (Bivand, Millo, and Piras 2021). <u>Model 1</u> includes the racial/ethnic composition variables—percent Black, percent Hispanic, percent Asian, and percent Native. <u>Model 2</u> includes the racial/ethnic composition variables and adds percent female headed households. <u>Model 3</u> includes the racial/ethnic composition variables and adds neighborhood deprivation scale. <u>Model 4</u> includes the racial/ethnic composition variables and adds percent female headed households and neighborhood deprivation scale.

Results

Descriptive Statistics

Descriptive statistics for the analytic sample are shown in Table 2.1. The mean LBW rate is about 5%, but rates vary substantially across census tracts with the minimum rate being 0% and the maximum being 13.3%. This variation can be seen visually in Figure 2.1, which shows quintile ranges of observed LBW rates for the census tracts included in the analysis. Relatively large concentrations of high LBW rates are seen in the central Los Angeles area (Map C) and the East Bay area (Map B).

Table 2.1. Descriptive Statistics of Analytic Sample (n=7,619)

	Mean	Median	Minimum	Maximum	SD	Moran's I[a]
LBW Rate (%)	5.006	4.920	0.000	13.330	1.576	0.287***
% Black	5.823	2.563	0.000	89.760	9.263	0.812***
% Hispanic	37.223	29.606	1.291	99.031	26.400	0.830***
% Asian	13.107	7.683	0.000	89.877	14.924	0.819***
% Native	0.421	0.264	0.000	37.457	0.900	0.391***
% FHH	14.179	13.305	0.600	58.545	6.388	0.718***
Neighborhood Deprivation Scale	0.000	-0.229	-1.638	3.980	1.000	0.719***

Notes: [a]A first-order queen adjacency spatial weights matrix was used to calculate Moran's I.
*** $p < 0.001$

Table 2.1 also shows that the racial/ethnic composition of census tracts ranges considerably. For percent Black and percent Asian these values range from 0 or near 0% to around 90%. Percent Hispanic ranges from just over 1% to just over 99%, while percent Native ranges from 0 to 37%. Percent female headed households also varies considerably across census tracts, ranging from 0% to 58.5%, with a mean value of 14%.

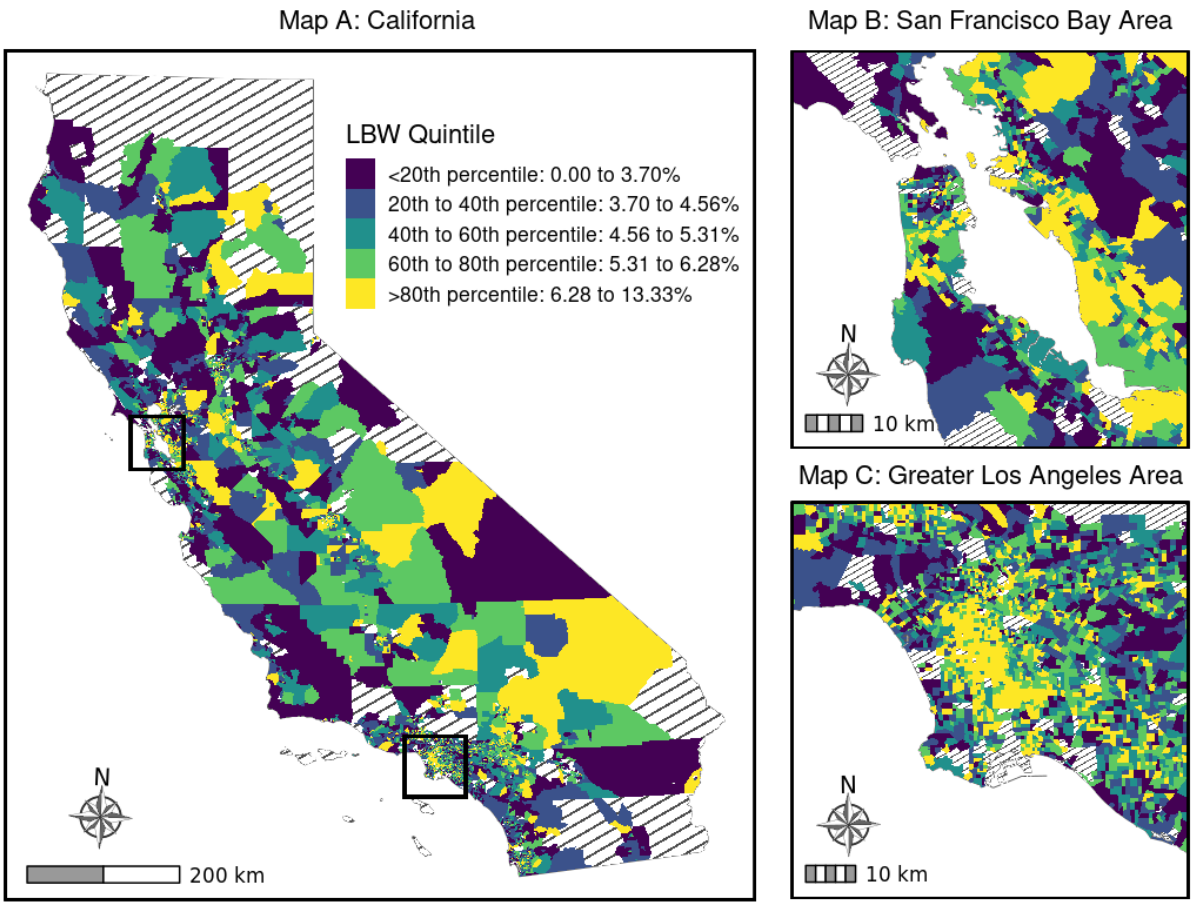

Figure 2.1. Quintile ranges of observed census tract low birthweight (LBW) rates in California, the San Francisco Bay Area, and the greater Los Angeles Area. Census tracts excluded from the analysis are represented with diagonal striped lines.

<u>Spatial Regression Analyses</u>

To start, I fit the OLS regression models. Given that these results are not central to the research aims, I present them as a supplementary table in Appendix A (Table A1). As expected, the Moran's I of the residuals for the OLS models indicated statistically significant spatial autocorrelation for all four models. Lagrange Multiplier diagnostics indicated that spatial lag models were appropriate.

Results from the spatial lag models are shown in Table 2.2. Two key statistics demonstrate the importance of using spatial lag models rather than OLS models in this case. First, the Moran's I of residuals for each of the spatial lag models is non-significant, suggesting that these models have successfully addressed the spatial dependence that was present in the OLS regression models. Second, the spatial autoregressive coefficient (rho) is statistically significant for all four spatial lag models, which further suggests that spatial dependence is not a problem in these models. Additionally, model coefficients for the spatial lag models are generally slightly smaller in magnitude than they were in the OLS models. This, in combination with the statistical significance of the spatial autoregressive coefficients, signals that the coefficients in the OLS models were slightly inflated due to spatial autocorrelation, but that this has been adequately addressed in the spatial lag models. Also of note is the multicollinearity condition number. Multicollinearity occurs when two or more independent variables in a model are highly correlated with one another and can lead to incorrect regression results. Multicollinearity is generally thought to be an issue if the multicollinearity condition number is above 15, but this number falls below this value for all four models, indicating that correlation between the independent variables is not an issue for these models.

Model 1 includes each of the racial/ethnic composition variables. An increased percentage of Black, Hispanic, Asian, and Native populations are all associated with a statistically significant higher LBW rate, but the magnitude of this effect varies across racial/ethnic groups. For percent Hispanic and percent Asian, a one percentage point increase in each of these populations is associated with about a 0.015 percentage point increase in LBW rate. The effect for percent Black population is much larger, with a one percentage point increase in Black population being associated with a 0.051 percentage point increase in LBW rate. Put another way, when comparing a census tract with 0% Black population (the lowest observed value) to one with 90% Black population (the highest observed value), the predicted increase in LBW rate is 4.6 percentage points. The effect for percent Native population is the largest, with a one percentage point increase in Native population being associated with a 0.087 percentage point increase in LBW rate. This translates to a 3.2 percentage point increase in LBW rate when comparing a census tract with 0% Native population (the lowest observed value) to a tract with 37% Native population (the highest observed value).

Table 2.2. Spatial lag regression results predicting low birthweight rates in California census tracts (n=7619)

Variable	Model 1	Model 2	Model 3	Model 4
% Black	0.051 ***	0.041 ***	0.048 ***	0.041 ***
	(0.002)	(0.002)	(0.002)	(0.002)
% Hispanic	0.015 ***	0.009 ***	0.008 ***	0.005 ***
	(0.001)	(0.001)	(0.001)	(0.001)
% Asian	0.016 ***	0.015 ***	0.014 ***	0.013 ***
	(0.001)	(0.001)	(0.001)	(0.001)
% Native	0.087 ***	0.070 ***	0.060 ***	0.052 **
	(0.018)	(0.018)	(0.018)	(0.018)
% FHH		0.032 ***		0.023 ***
		(0.004)		(0.005)
Neighborhood Deprivation Scale			0.230 ***	0.189 ***
			(0.027)	(0.029)
Intercept	2.730 ***	2.614 ***	3.122 ***	2.968 ***
	(0.075)	(0.077)	(0.088)	(0.094)
Rho	0.237 ***	0.226 ***	0.224 ***	0.218 ***
	(0.017)	(0.017)	(0.017)	(0.017)
Log Likelihood	-13163.508	-13137.917	-13128.287	-13116.254
Akaike information criterion (AIC)	26341.016	26291.834	26272.574	26250.508
AIC difference from OLS model	-210.947	-190.210	-186.516	-176.572
Multicollinearity Condition Number	5.174	10.242	8.379	11.120
Moran's I of Residuals[a]	-0.006	-0.007	-0.008	-0.008

Notes: *** p < 0.001; ** p < 0.01; * p < 0.05. Standard errors are in parentheses.
[a]A first-order queen adjacency spatial weights matrix was used to calculate the Moran's I.

Model 2 adds percent female headed households (FHH). This is positively associated with LBW rate with a one percentage point increase in FHH predicting a 0.032 percentage point increase in LBW. Further, percent FHH appear to account for some of the racial/ethnic composition effects. The effect of each racial/ethnic composition variable decreases slightly with percent FHH added, with the exception of percent Asian which remains about the same, suggesting that the relationship between percent Asian and LBW rate is not affected substantively by percent FHH.

Model 3 includes racial/ethnic composition and neighborhood deprivation scale. Neighborhood deprivation scale is positively associated with LBW rate, with a one-point increase on the scale predicting a 0.23 percentage point increase in LBW rate. Further, as in Model 2, the racial/ethnic composition effects decrease by varying amounts, suggesting that neighborhood deprivation accounts for some of the relationship between racial/ethnic composition and LBW rate, particularly for percent Hispanic and percent Native.

Model 4 adds both percent FHH and neighborhood deprivation scale. As in Models 2 and 3, both of these variables are positively associated with LBW rate but are slightly smaller in magnitude than they were when added individually, likely due to the correlation between these two variables. A one percentage point increase in FHH is associated with a 0.023 percentage point increase in LBW rate and a one-point increase in neighborhood deprivation scale is associated with a 0.189 percentage point increase in LBW rate. The racial/ethnic composition coefficients are all smaller in magnitude in Model 4 than they were in Model 1, and with the exception of percent Black, they are all smaller when percent FHH and neighborhood deprivation are added together than in the two models when they are added individually. This suggests that percent FHH and neighborhood deprivation each play an independent role in accounting for the relationship between racial/ethnic composition and LBW rate. However, the relationship between these variables does not appear to be uniform across racial/ethnic groups.

When looking at percent Black, the coefficient in Model 4 is somewhat lower than it was in Model 1 but is the same as in Model 2. This seems to suggest that percent FHH and neighborhood deprivation account for some of the relationship between percent Black and LBW rate but are likely closely intertwined for Black communities. For percent Hispanic, percent FHH and neighborhood deprivation appear to have the largest attenuating effect as the coefficient in Model 4 is one third as large as it was in Model 1. Percent FHH and neighborhood deprivation also appear to account for some of the relationship between percent Native and LBW rate, with the coefficient in Model 4 being about one third smaller than it was in Model 1. Interestingly, the coefficient for percent Asian in Model 4 is only slightly smaller than in Model 1. This suggests that percent FHH and neighborhood deprivation play a small role in the relationship between percent Asian and LBW rate, but this relationship appears to be largely driven by factors not included in this analysis. Despite female headed households and neighborhood deprivation accounting for some of the relationship between racial/ethnic composition and LBW rate, a strong relationship remains, particularly for percent Black and percent Native.

Also of note in Table 2.2 is the Akaike information criterion (AIC). The AIC for each of the spatial lag models is lower than the AIC for the corresponding OLS models, suggesting that the spatial lag models are a better fit. Further the AIC decreases when percent FHH and neighborhood deprivation scale are added and is lowest in Model 4, suggesting that Model 4 is a better fitting model.

To identify vulnerable areas for future consideration and intervention, I identified census tracts that had high LBW rates and low residuals for Model 4. Specifically, I included tracts that were in the highest quintile for observed LBW rate and that had standardized residuals within one standard deviation from the mean. Figure 2.2 shows the census tracts (n=631) that met these criteria. There are several pockets of high LBW/low residual tracts across the state. Of particular interest are the central Los Angeles and East Bay areas, which each contain a relatively high concentration of high LBW/low residual tracts, suggesting these are vulnerable areas that warrant further consideration.

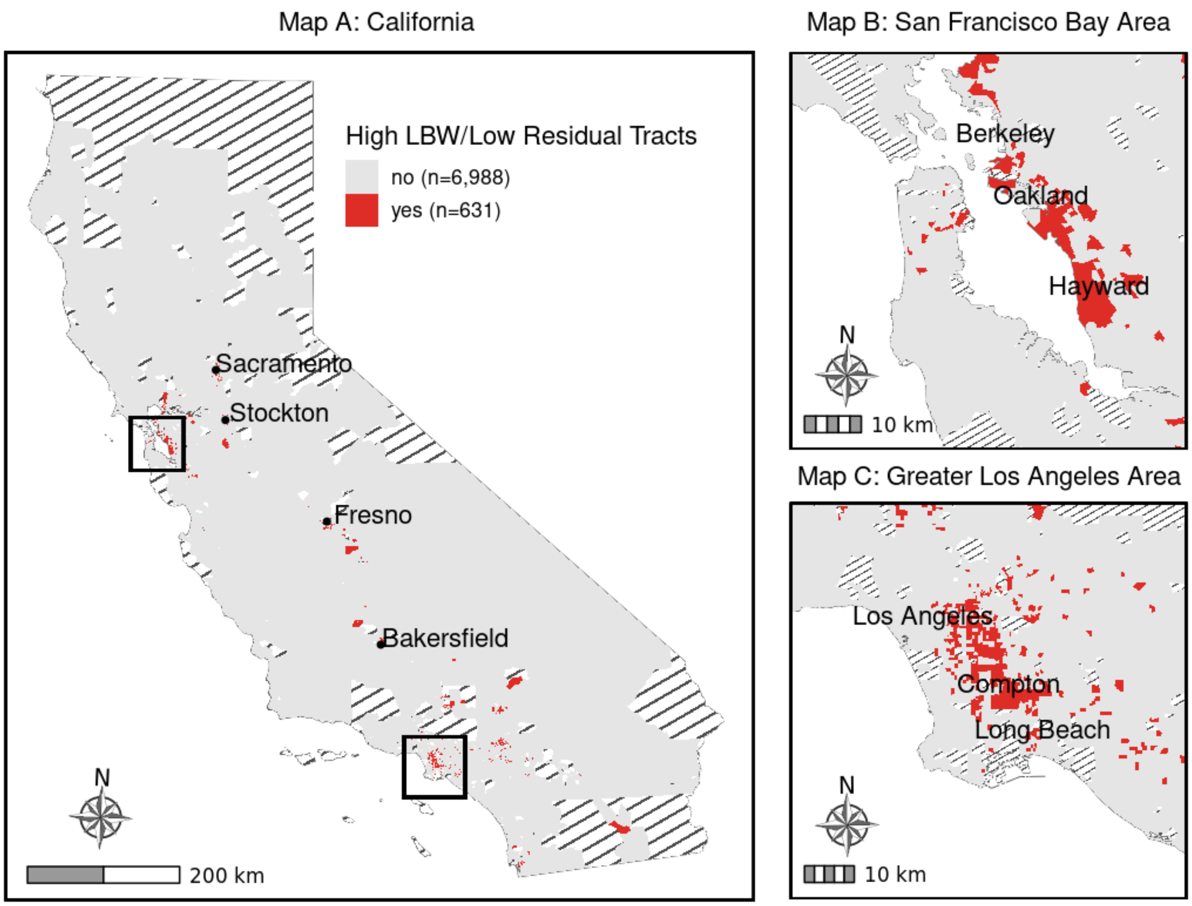

Figure 2.2. Map of census tracts that are in the highest quintile range for observed low birthweight rate and have Model 4 residuals within one standard deviation of the mean. Census tracts excluded from the analysis are represented with diagonal striped lines.

Discussion

In this analysis, I utilized spatial lag regression models to look at the relationship between racial/ethnic composition and LBW rate across California census tracts and considered the role of family structure and neighborhood deprivation in this relationship.

Findings show that predicted census tract LBW rate increases as the proportion of Black, Hispanic, Asian, and Native populations increase. However, this effect is not uniform across racial/ethnic composition groups and appears particularly large for percent Black and percent Native. This is consistent with prior findings that LBW rates are higher in Black communities (Liévanos 2019; Morenoff 2003). Further, spaces in which elevated proportions of Black and Native individuals are found may also contain multiple stressors linked to structural racism and racial segregation which may contribute to the elevated rates of LBW found in these spaces. The smaller effects of percent Hispanic and percent Asian are likely due in part to the heterogeneity within these groups and may reflect the "healthy immigrant paradox" (Acevedo-Garcia et al. 2007; Bender and Castro 2000). Future research should consider how differences in immigration status and country of origin affect racial/ethnic composition effects on LBW rates for these groups.

Further, a higher proportion of female headed households and increased neighborhood deprivation are both associated with higher predicted LBW rates. These variables are closely related, but both remain statistically significant even when added to the model together, suggesting that each plays an independent role in the relationship between racial/ethnic composition and LBW rate. This is consistent with prior research demonstrating that family structure is an important mechanism through which inequalities are reproduced (Liévanos et al. 2021; McLanahan and Percheski 2008).

Family structure and neighborhood deprivation appear to attenuate some of the racial/ethnic composition effects. However, this is not uniform across racial/ethnic groups. The effect of percent Black remains relatively large after percent female headed households and neighborhood deprivation are added and although the effect of percent Native decreases a fair amount when these variables are added, this effect remains quite large. This suggests that other variables not included in this analysis are driving the relationship for percent Black and percent Native and should be investigated in future research. The effect for percent Hispanic drops considerably when these variables are added, suggesting that the relationship between percent Hispanic and LBW rate is largely driven by these variables. This is consistent with prior work that demonstrates that in the state of California, tract-level Latinx composition is associated with concentrated socioeconomic disadvantage and that isolated Latinx economic disadvantage is associated with higher risk of exposure to fine particulate matter air pollution (Liévanos 2019b).

Perhaps surprisingly, the effect of percent Asian only decreases slightly when percent female headed households and neighborhood deprivation are added. It is not entirely clear why this is the case, but it is consistent with prior work that found percent Asian population to be associated with higher concentrations of fine particulate matter air pollution across California census tracts, even when controlling for neighborhood disadvantage (Liévanos 2019b). Many factors outside the scope of this analysis, such as exposure to environmental hazards, access to healthcare, and availability of healthy foods, likely play a role in the relationship between racial/ethnic composition and LBW inequalities at the community level and should be considered by future work.

As part of the analysis, I also identified areas with a high number of census tracts that have high LBW rates and low residuals for the full model. Two areas stood out as particularly vulnerable—the central Los Angeles area and the East Bay area—suggesting that these and other disadvantaged areas should be targeted by policies and interventions designed to promote better outcomes for mothers and babies. Further, findings highlight the importance of ongoing support for programs like California's Black Infant Health Program that aims to improve health among Black mothers and babies by connecting Black women with vital care and support during and after pregnancy. Similar programs should be developed for other high-risk groups and should target communities with characteristics demonstrated to be associated with higher risk of LBW, including those with high racial/ethnic minority population, high proportion of female headed families, and high neighborhood deprivation.

This analysis is not without limitations. Although findings revealed important patterns about the relationship between racial/ethnic composition and LBW rates at the neighborhood level, conclusions cannot be made about how these relationships operate at the individual level. Future research should consider how individual-level racial/ethnic identity interacts with neighborhood-level contexts to influence LBW.

Linking CalEnviroScreen data with individual-level birth data for the state of California would be a great way to further explore the patterning of racial/ethnic inequalities in LBW. Morenoff (2003) previously identified neighborhood stress and adaptation mechanisms as predictors of individual-level risk of LBW in Chicago. Future work could investigate these mechanisms for the state of California to see if the same patterns hold true. Further, utilizing the CalEnviroScreen data to explore the effect of environmental exposures on individual-level birth outcomes would build on prior research linking various environmental exposures to LBW risk including lead, air pollution, toxic air contaminants, traffic pollution, pesticides, and polychlorinated biphenyls (PCBs) (August 2021; Faust 2017; Rich et al. 2015).

Additionally, future research should consider the non-stationarity in the relationship between racial/ethnic composition and LBW rate by looking at how this relationship varies across space. For instance, utilizing geographically weighted regression to follow up on the current analysis would provide insight into whether the observed patterns are generally uniform across the state or if they vary due to place-specific social and historical contexts. This type of analysis could also help further identify areas of interest for future research.

CHAPTER III

A MULTILEVEL ANALYSIS OF RACIAL/ETHNIC INEQUALITIES IN LOW BIRTHWEIGHT

Introduction

Low birthweight (LBW) inequalities in the U.S. are patterned by race/ethnicity (Alhusen et al. 2016; Almeida et al. 2018; Lu and Halfon 2003; Womack 2018) and are geographically concentrated with disproportionately high rates in Black communities (Liévanos 2019b; Morenoff 2003). LBW is an important biomarker of infant health as it is associated with a higher risk of infant mortality (Pusdekar et al. 2020) and several health and developmental outcomes later in life, including asthma, hypertension, and diabetes (Barker et al. 2002; Choi and Martinson 2018; Hassan et al. 2021; Nepomnyaschy and Reichman 2006). Further, LBW is associated with lower socioeconomic attainment later in life (Bilgin et al. 2018) suggesting that it may be one way that disadvantage is transmitted intergenerationally.

Social conditions, such as race/ethnicity and segregation, operate as "fundamental causes" of health inequalities by affecting exposure to risk factors that can influence health and by affecting access to resources that can mitigate the effects of disease if it does occur (Link and Phelan 1995; Phelan and Link 2015; Williams and Collins 2001). Race/ethnicity and segregation can function as fundamental causes of LBW at both the individual and neighborhood levels in several ways including stress (Turner 2010; Wadhwa et al. 2011), exposure to hazardous environments (Rich et al. 2015), and access to quality healthcare (Shi 2004).

Despite an abundance of research that show a link between race/ethnicity and racial/ethnic composition and the risk of LBW, this research often focuses on either the individual level *or* the neighborhood level and may miss important information about how these inequalities are patterned. Research that focuses on the neighborhood level cannot tell us about individual-level patterns and research that focuses on the individual level may miss information about how neighborhood contexts effect individuals with different social identities in different ways. Further, research that focuses on compositional effects may inadvertently suggest that living among higher concentrations of some groups is bad for one's health.

To address these gaps in the literature and to add to the understanding of how racial/ethnic health inequalities are patterned, I use nationally representative data to conduct a multilevel analysis look at how individual-level race/ethnicity and neighborhood-level racial/ethnic composition shape LBW risk separately, additively, and interactively. To assess to what extent inequalities are being driven by individual-level race/ethnicity and to what extent they are being driven by neighborhood-level racial/ethnic composition, I fit a series of additive models where I look at the individual and compositional effects of race/ethnicity—first separately and then together. I then consider whether living in a neighborhood with a higher percentage of one's own race/ethnicity provides a protective effect for LBW and if this varies across racial/ethnic groups. To do this, I fit a series of models that allow the two levels to interact.

Results indicate that individual-level Black racial identity and higher neighborhood-level Black composition are both associated with higher risk of LBW. However, the neighborhood composition effect appears to be driven by an accumulation of individual-level risk. Further, for

Black mothers, but not mothers of other racial/ethnic identities, there appears to be a protective effect from living in a neighborhood with a higher percentage of one's own race/ethnicity.

Literature Review

Research that seeks to understand health inequalities often focuses on either the individual level *or* the neighborhood level. This holds true when looking at disparities in LBW. For instance, at the individual level, risk of LBW is patterned by racial/ethnic identity (Alhusen et al. 2016; Almeida et al. 2018; Womack 2018) with Black women in particular having disproportionately high risk of LBW compared to women in other racial/ethnic groups (Lu and Halfon 2003). Further, LBW is patterned by SES, with higher risk of LBW among mothers with less education (Jansen et al. 2008) and with lower household incomes (Finch 2003). Research at the neighborhood or community level has shown that LBW is concentrated geographically, with rates particularly high among Black and low-income communities (Liévanos 2019b; Morenoff 2003).

Focusing on the individual level can tell us important information about how health inequalities occur but may miss important processes and context that occur at the neighborhood or community level. However, focusing on the neighborhood level may result in an ecological fallacy in which an inaccurate assumption is made that patterning of inequality at the neighborhood level is an indication of individual-level inequality. Robinson's (1950) influential work demonstrated that a correlation between two variables can be different at the individual and ecological levels. Further, Subramanian et al. (2009) demonstrated that there are perils presented not only by the ecological fallacy, but also by the individualistic fallacy, and they argued for the necessity of historically informed multilevel thinking. It is likely that LBW inequalities are shaped by both individual-level social identities and neighborhood-level contexts simultaneously so studying how both levels interact to shape inequalities is important to better support mothers and babies. Further, considering both levels simultaneously allows for the exploration of differential effects of neighborhood contexts for individuals from different racial/ethnic groups.

LBW is a commonly used biomarker of infant health. It is an apt measure for looking at the patterning and production of health inequalities because it is an indicator of social determinants that affect health such as maternal race/ethnicity (Alhusen et al. 2016; Almeida et al. 2018; Choi and Martinson 2018; Geronimus 1996; Lu and Halfon 2003). LBW is a predictor of higher risk of infant mortality (Pusdekar et al. 2020) and several health and developmental outcomes in childhood and adulthood, including asthma, hypertension, and diabetes (Barker et al. 2002; Choi and Martinson 2018; Hassan et al. 2021; Nepomnyaschy and Reichman 2006). Further, LBW is associated with lower socioeconomic attainment later in life (Bilgin et al. 2018), suggesting that it may be one way that disadvantage is transmitted intergenerationally.

<u>LBW at the Individual Level</u>

Fundamental causes theory (Link and Phelan 1995) posits that social conditions, such as socioeconomic status, operate as fundamental causes of health disparities by affecting exposure to risk factors that influence health and by affecting access to resources that that minimize the effects of disease if it does occur. Phelan and Link (2015) argue that racism is a fundamental cause of racial health inequalities. This is in part due to racial differences in SES, but racism also operates as a fundamental cause independently through inequalities in power, prestige, freedom, neighborhood context, and health care.

Krieger's ecosocial theory (Krieger 2001, 2011) complements a fundamental causes perspective by arguing that the material and social world in which we live becomes biologically incorporated, or embodied, throughout our lives and leads to health inequalities. This occurs through several pathways of embodiment, including economic and social deprivation, toxic substances and hazardous conditions, socially inflicted trauma, and inadequate health care. Gravlee (2009) also describes the process of embodiment, detailing how racial inequality becomes embodied in the biology of racialized groups and individuals and leads to racial inequalities in a variety of health outcomes.

Stress is an important mechanism that influences birth outcomes (Turner 2010; Wadhwa et al. 2011). Geronimus (1996) concluded that racial/ethnic inequalities in LBW can occur when racially/ethnically minoritized individuals experience chronic activation of psychosocial stress pathways caused by exposure to discrimination, environmental hazards, and other stressors. These experiences become embodied in the form of premature biological aging or "weathering" (Geronimus et al. 2006). Black mothers in particular experience a weathering effect that leads to higher risk of LBW than white mothers at all ages as well as a different shaped relationship between age and LBW risk.

This is supported by Lu and Halfon's (2003) review of studies on racial and ethnic disparities in birth outcomes in which they found that poor birth outcomes, including low birthweight, are disproportionately high among Black women compared to Hispanic and non-Hispanic white women. They propose that these disparities in birth outcomes result from differences in developmental trajectories that start with early life experiences and differences in cumulative exposure to stressors over the life course. Further, Koning and Ehrenthal (2019) find that low-income and racial minority women have a higher risk of preterm birth and LBW in part due to a higher likelihood of experiencing "stressor landscapes."

LBW at the Neighborhood Level

Many of the factors that influence low birthweight occur at the neighborhood level including stress (Turner 2010; Wadhwa et al. 2011), exposure to hazardous environments (Rich et al. 2015), and access to quality healthcare (Shi 2004). Further, Morenoff (2003) found that, in the case of Chicago, neighborhood-level stress and adaptation mechanisms were predictors of individual-level risk of LBW. Specifically, prolonged exposure to neighborhood-level violent crime was associated with greater risk of LBW, while neighborhood social relationships and engagement were associated with a lower risk of LBW.

These processes may disproportionately impact racial/ethnic minority communities through residential segregation. Williams and Collins (2001) identified segregation as a fundamental cause of racial health inequalities. They argue that this occurs in part because residential segregation affects access to education and employment opportunities which leads to racial differences in SES which then lead to racial differences in health. Further, they argue that segregation also leads to differences in social and physical conditions that affect health. Prior research has linked residential segregation to adverse birth outcomes (Mehra et al. 2017). Krieger et al. (2020) found evidence that historical redlining in New York City may be a determinant of present-day preterm birth risk and De Maio et al. (2017) found a significant association between racial/ethnic segregation and LBW in Chicago.

Further, Krieger's pathways of embodiment include processes that occur at the neighborhood and community level including residential and occupational segregation that lead to racial inequalities in economic deprivation and inequalities in risk of exposure to toxic substances, such as air pollution and lead paint. When looking at adverse birth outcomes, some of the ways that embodiment may occur and affect outcomes at the neighborhood level include access to quality prenatal care, exposure to environmental toxins, and stress (Krieger et al. 2020).

LBW at Multiple Levels

Although most research that has looked at racial/ethnic inequalities in LBW has focused on either the individual or the ecological level, there are some exceptions. For instance, using U.S. birth data from 1990, Gorman (1999) found that at the county level, the percent of the population that was foreign-born, the percent of families that were female headed, and median household income affected risk of LBW. However, the effects of these variables differed across racial/ethnic groups. Specifically, higher foreign-born population and higher median household income were associated with a decreased risk of LBW for Mexican and white Americans but had no effect for Puerto Rican and Cuban Americans. Further, a higher percentage of female headed families was associated with a higher risk of LBW for all groups but was strongest for Cuban and Puerto Rican Americans.

In a review of studies on racial residential segregation and birth outcomes, Mehra et al. (2017) found that segregation was associated with an increased risk of preterm birth and LBW for Black mothers. Further, Walton (2009) found that segregation is associated with a decreased risk of LBW for Asian Americans, no effect among Latino Americans, and a small increase in risk for African Americans, but only in the presence of higher poverty rates. Despite these studies, there is still much that is not understood about the patterning of racial/ethnic LBW inequalities at multiple levels.

Research Aims

In this analysis, I add to the understanding of how racial/ethnic health inequalities are patterned at multiple levels by utilizing multilevel models to look at how individual-level race/ethnicity and neighborhood-level racial/ethnic composition shape LBW risk separately, additively, and interactively. I address two main research questions:

1. To what extent are racial/ethnic disparities in LBW being driven by individual-level race/ethnicity and to what extent are they being driven by neighborhood-level racial/ethnic composition?
2. Does living in a neighborhood with a high percentage of the population belonging to one's own racial/ethnic group provide a protective effect for risk of LBW? If so, does this effect vary across racial/ethnic groups?

Data and Methods

Data

Data comes from the restricted-use National Longitudinal Study of Adolescent to Adult Health (Add Health) (Harris et al. 2019). Add Health is a large longitudinal survey of a nationally representative sample of U.S. adolescents who were in grades 7-12 during the first wave of data collection (1994-95). Respondents have been followed for five waves of data collection, with the most recent occurring in 2016-18 when respondents were aged 33-43.

Wave 5 contains information about births that occurred for respondents and their partners. My analysis utilizes this birth data along with demographic data from all waves. Wave 5 contained data for 11,122 births to female respondents. My analysis includes 9,652 births that occurred between 1990 and 2018 for which birthweight data and census tract pseudo FIPS codes were available. Rather than drop cases that were missing data on the key independent variables or the control variables, I chose to impute missing values using multiple imputation. I used the mice package in RStudio (van Buuren and Groothuis-Oudshoorn 2011) to impute 5 datasets. Of the key independent variables, no cases were missing data for individual-level race/ethnicity and 81 cases (0.84%) were missing data for census tract racial/ethnic composition. Information on number and percent of missing cases for control variables is shown in Table 3.1.

Dependent Variable

Low birthweight is a dichotomous variable coded as 1=yes is the baby weighed less than 5.5 pounds or 0=no if the baby weighed 5.5 pounds or more. To code this variable, I used birthweight data provided by Add Health respondents. They were first asked to report the birthweight of the baby. If they did not know, they were asked a follow-up question of whether the baby was more or less than 5.5 pounds. When available I used the former to determine whether the baby was LBW, otherwise I used the latter. About 8.76% of births in the sample were LBW.

Key Independent Variables

Individual-level *race/ethnicity* comes from Wave 5, except for 32 cases that were missing this information in this wave. In these instances, I utilized Wave 1 race/ethnicity data instead. Add Health respondents had the option to identify with more than one racial/ethnic category. In these cases, they were asked to choose the one category that they most strongly identified with. I use these responses when applicable. I utilize five race/ethnicity categories that correspond with the categories used for the neighborhood racial/ethnic composition variables available in the Add Health data. The categories are: white, Black, Hispanic, Asian/Pacific Islander (Asian/PI), and other, which includes respondents who indicated other (either initially or when asked to choose a single identity after selecting more than one initially) or American Indian/Alaska Native for their racial identity.

Neighborhood *racial/ethnic composition* variables are based on data for the census tract in which the mother was residing at the wave of data collection prior to the date of the birth. These variables are a measure of the percent of the population that belongs to each racial/ethnic category. I utilize four racial/ethnic composition variables: percent non-Hispanic Black, percent Hispanic, percent non-Hispanic Asian (including Pacific Islander), and percent non-Hispanic other which includes other, two or more races, and American Indian/Alaska Native (hereafter percent Black, percent Hispanic, percent Asian, and percent other). These four categories, along with percent white, add up to 100 percent for each census tract.

<u>Control Variables</u>

I include controls for maternal age, educational attainment, and nativity status, as well as multiple gestation and census tract median household income. Controlling for these variables removes the effect of potential compositional differences. For instance, if twins are more common among some racial/ethnic groups, this may elevate the predicted risk of LBW for those groups given that twins' risk of LBW is 10.3 times greater than singletons' (Luke and Keith 1992). This allows us to see if observed inequalities between social strata are driven by these variables or if the inequalities persist even after accounting for them.

Maternal age is measured by subtracting the birthdate of the baby from the mother's birthdate. I include age and age-squared in the models to account for the non-linear relationship between maternal age and LBW (Evans et al. 2023; Geronimus 1996).

Maternal *educational attainment* is a measure of the highest level of education that the mother had achieved prior to the date of the birth. I constructed three educational attainment categories: less than high school (HS) if the mother had not earned a high school diploma or equivalent, HS diploma if the mother had earned a high school diploma or equivalent (including GED), and bachelor's+ if the mother had earned a bachelor's degree or higher.

U.S. born is a dichotomous measure indicating whether the mother was born in the U.S. or somewhere else.

Multiple gestation was coded as singleton, twins, or triplets+.

Neighborhood *median household income* is a measure of the median household income (in $1,000s) for the census tract in which the mother resided at the wave of data collection prior to the date of birth. I adjusted all median household income values to be equivalent to 2008 dollars. A logged version of median household income was used in the models.

<u>Methodological Approach</u>

I utilize Bayesian logistic multilevel models in which individuals are nested in census tracts. The restricted use Add Health data includes pseudo FIPS codes for the respondents' location of residence. While these codes do not allow for merging with other spatial data, they do allow for grouping of respondents who live in the same spatial units. I utilize census tract pseudo FIPS codes to group respondents living in the same census tracts. The amount of census tract clustering is relatively small, but notable. The minimum number of respondents in a census tract is 1, while the maximum is 30. The mean number of respondents in observed census tracts is 2.67 and the median is 2.

All models were fit in RStudio using the brm_multiple command from brms library (Burkner 2017). brm_multiple is well-suited for analyses with imputed data as it runs the model for each imputed dataset then pools the results. Models were fit with a burn-in of 5,000 iterations and a total length of 50,000 iterations (with thinning every 50 iterations).

The general equation for the logistic multilevel models is:

$$log \frac{\pi_{ij}}{(1 - \pi_{ij})} = \beta_0 + \beta_\alpha x_{ij} + \mu_{0j}$$

$$\mu_{0j} \sim N\left[0, \sigma_{\mu_0}^2\right]$$

where π_{ij} is the probability of birth i in in census tract j being LBW, β_0 is the intercept, x_{ij} is a vector of explanatory variables, and β_α is a vector of associated parameter values. μ_{0j} is the census tract-level random effect, which is normally distributed with mean 0 and variance $\sigma_{\mu_0}^2$.

To assess model goodness-of-fit, I calculate the LOO (leave-one-out cross-validation) information criterion (LOOIC) using the loo package in R (Vehtari et al. 2024). The LOOIC is comparable to the Akaike Information Criterion (AIC) used for frequentist approaches, but is designed for use with Bayesian models as it takes into account model priors and the posterior distribution (Vehtari, Gelman, and Gabry 2016).

To address my first research question that asks to what extent are racial/ethnic disparities in LBW being driven by individual-level race/ethnicity and to what extent are they being driven by neighborhood-level racial/ethnic composition, I fit four logistic multilevel models with LBW as the dependent variable.

<u>Model 1</u> includes individual-level race/ethnicity. This model indicates how LBW is patterned by individual racial/ethnic identity without accounting for compositional effects.

Model 2 includes census tract-level racial/ethnic composition. This model shows how LBW is patterned by the racial/ethnic composition of the census tract where the mother resides, without accounting for individual-level racial/ethnic identity.

Model 3 includes individual-level race/ethnicity *and* census tract-level racial/ethnic composition. By including variables at both levels, this model evaluates if compositional effects are being driven by an accumulation of individual-level effects or if there are independent compositional effects.

Model 4 is the same as Model 3 with control variables added. This model assesses if the effects of individual and compositional race/ethnicity on LBW are explained by maternal age, educational attainment, and nativity, multiple gestation, and census tract median household income.

To address my second research question that asks if there is a protective effect for living in a neighborhood with a high percentage of one's own racial/ethnic group, I fit a series of models with interaction terms. First, I consider the interaction between each racial/ethnic group and its "ego" composition:

Model 5 includes individual-level racial/ethnic identity, census tract racial/ethnic composition, and an interaction between each racial/ethnic identity and its ego composition. In this model the main effects of race/ethnicity and the corresponding interactions are relative to white mothers (the omitted category). In other words, the interaction effect indicates the difference in the compositional effect for mothers with the indicated racial/ethnic group compared to the effect for white mothers. Further, the interaction between each racial/ethnic identity and its corresponding ego composition provides an indication of whether there is a protective effect, harmful effect, or no effect for living in a neighborhood with a higher percentage of one's own race/ethnicity.

Model 6 is the same as Model 5 with control variables added to see how the control variables affect the relationships.

Results from Models 5 indicate that the only statistically significant interaction is for Black racial identity and composition. To further explore this, I consider this interaction alone, without any other racial/ethnic identities or compositions included:

Model 7 includes individual-level Black racial/ethnic identity, census tract percent Black composition, and an interaction between the two. In this model, the main effect of Black racial identity and the interaction effect is no longer relative to white mothers, but is now relative to all non-Black mothers. In other words, the interaction effect indicates the difference in the effect of Black composition on Black mothers compared to non-Black mothers.

Model 8 is the same as Model 7 with control variables added.

I also fit a version of the model with every possible interaction between individual race/ethnicity and census tract racial/ethnic composition to see if there were any other significant interactions that warranted further investigation. Results were similar to the results of Models 5 and 6 and no other significant interactions were present. Further, LOOIC statistics were higher for these models indicating worse goodness-of-fit. So rather than include these results with the main models, I present them as a supplementary table in Appendix B (Table A2).

Results

Descriptive statistics are shown in Table 3.1. 8.67% of births were classified as LBW (less than 5.5 lbs.) About 60% of births were to white mothers, about 22% were to Black mothers, about 12% were to Hispanic mothers, about 4% were to Asian/PI mothers, and about 1% were to mothers in the “other” race/ethnicity category. Further, there is considerable variation in census tract racial/ethnic composition. Percent Black ranges from 0 to 100%, percent Hispanic ranges from 0 to 97%, percent Asian ranges from 0 to 74%, and percent other ranges from 0 to 82%. The mean maternal age was 27.18 years. A little over half of the births were to mothers with a high school diploma or equivalent, about 30% were to mothers with a bachelor’s degree or higher, and about 9% were to mothers with less than a high school education. About 92% of births were to mothers who were born in the U.S. and about 97% were singleton births. The mean census tract median household income in which mothers resided during the wave of data collection prior to the birth was about $48,000 and ranged considerably from $7,280 to $168,800.

The results of the first set of logistic regression models are shown in Table 3.2. Model 1 includes just the individual-level race/ethnicity categories. Black mothers, Hispanic mothers, and “other” mothers are each predicted to have higher risk of LBW than white mothers, while Asian/PI mothers are predicted to have lower rates. However, the only effects that are statistically significant are those for Black and “other”. The risk of LBW for Black mothers is predicted to be 2 times higher than the risk for white mothers and the risk for “other” mothers is predicted to be over 4 times higher. While it is not possible to draw strong conclusion about the effect of “other” since this category encompasses multiple racial/ethnic identities, it is likely that the large effect is driven at least in part by the effect the American Indian/Alaska Native (AI/AN) category that is included in this group because about 64% of "other" mothers are AI/AN. Model 2 includes just the census tract racial/ethnic composition variables. Once again, the only statistically significant effect is associated with the Black racial identity and a one percentage point increase in Black population is associated with a 0.7% increase in the risk of LBW.

Table 3.1. Descriptive statistics of sample (*n*=9,652 births)

Variable	*n*	%				*n* Missing	% Missing
LBW						0	0
Yes	837	8.67					
No	8,815	91.33					
Race/Ethnicity						0	0
White	5,853	60.64					
Black	2,139	22.16					
Hispanic	1,161	12.03					
Asian/PI	396	4.10					
Other	103	1.07					
Racial/Ethnic Composition	Mean	SD	Median	Min	Max	81	0.84
% Black	17.17	25.70	4.98	0.00	100.00		
% Hispanic	12.59	19.84	3.54	0.00	97.40		
% Asian	4.49	9.38	1.11	0.00	74.38		
% Other	1.91	3.17	1.10	0.00	82.06		
Controls							
Maternal Age	27.18	5.56	27.25	13.50	40.92	0	0
CT Median Household Income (in $1,000s)	48.09	21.08	45.40	7.28	168.80	83	0.86
Educational Attainment	*n*	%				834	8.64
Less than HS	896	9.28					
HS Diploma or GED	4,974	51.53					
Bachelor's Degree or Higher	2,948	30.54					
U.S. Born						275	2.85
Yes	8,854	91.73					
No	523	5.42					
Multiple Gestation						16	0.17
Singleton	9,320	96.56					
Twins	312	3.23					
Triplets+	4	0.04					

Model 3 includes both the individual-level race/ethnicity categories and the census tract racial/ethnic composition variables. In this model, the effect of percent Black decreases in magnitude and is no longer statistically significant, while the effect of individual-level Black racial identity remains statistically significant and similar in magnitude to what it was in Model 1. This suggests that the neighborhood-level effect of percent Black on LBW risk in Model 2 is being driven by the aggregation of individual-level effects. The effect of the individual-level "other" racial category remains large and significant. Again, it is not clear what this means, but it is likely driven at least in part by the AI/AN group, although I am not able to determine what share of "percent other" identify as AI/AN.

Model 4 adds controls for maternal age, educational attainment, and nativity status, as well as multiple gestation and census tract median household income. As expected, higher maternal educational attainment and multiple gestation are associated with higher risk of LBW. Maternal age and nativity status do not have statistically significant effects, perhaps due to the differential relationship between age and LBW across different racial/ethnic groups (Evans et al. 2023; Geronimus 1996) and the complex relationship between immigration status and birth outcomes (Acevedo-Garcia, Soobader, and Berkman 2005; Bender and Castro 2000). Interestingly, when the control variables are added, the effect of individual-level Black racial identity remains statistically significant and in fact increases in magnitude. This suggests that there may be other factors responsible for Black mothers' high risk of LBW that are not accounted for in this analysis.

Table 3.2. Multilevel logistic regression results from additive models predicting low birthweight

	Model 1			Model 2			Model 3			Model 4		
	OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI	
Race/Ethnicity												
Black	2.002	1.579	2.547				1.978	1.454	2.724	2.106	1.553	2.835
Hispanic	1.024	0.747	1.402				0.900	0.600	1.340	0.961	0.633	1.435
Asian/PI	0.885	0.517	1.486				0.879	0.487	1.598	0.993	0.529	1.790
Other	4.145	1.988	8.802				3.725	1.704	7.885	4.402	2.092	8.971
Racial/Ethnic Composition												
% Black				1.007	1.003	1.011	1.000	0.995	1.005	0.998	0.993	1.003
% Hispanic				1.003	0.998	1.008	1.004	0.998	1.010	1.002	0.996	1.009
% Asian				0.992	0.980	1.004	0.993	0.980	1.006	0.995	0.981	1.007
% Other				1.026	0.998	1.054	1.022	0.992	1.051	1.017	0.987	1.046
Controls												
Age										0.996	0.974	1.016
Age^2										1.001	0.998	1.004
HS Diploma										0.740	0.521	1.057
Bachelors+										0.649	0.425	0.976
US Born										0.878	0.547	1.406
Twins										38.091	26.629	55.701
Triplets+										56.036	2.271	2069.371
Median HH Income (logged)										0.876	0.670	1.148
Intercept	0.035	0.028	0.043	0.035	0.027	0.044	0.032	0.025	0.041	0.074	0.022	0.249
LOOIC	5278.5			5299.0			5278.6			4917.0		

Notes: n=9,652 births, OR=odds ratio, 95% CI=95% credible interval, LOOIC=leave-one-out cross-validation information criterion. Reference categories are white for Race/Ethnicity, less than high school for educational attainment, foreign born for nativity, and singleton for multiple gestation.

The results from the second set of logistic regression models are shown in Table 3.3. These models explore the interactions between each racial/ethnic group and its corresponding ego composition and evaluate the possibility of a protective effect of living in a neighborhood with a higher percentage of one's own racial/ethnic group.

Model 5 includes individual-level race/ethnicity, census tract racial/ethnic composition, and an interaction between each individual-level racial/ethnic identity and its ego composition variable. There is a statistically significant interaction effect when Black is interacted with percent Black. In fact, the effect of percent Black is associated with an increased risk of LBW for white mothers, while it is associated with a slight decreased risk of LBW for Black mothers. This suggests that for white mothers, living in a higher percent Black neighborhood is associated with a higher risk of LBW, but for Black mothers, living in a higher percent Black neighborhood provides a protective effect for risk of LBW.

The interaction effects are not significant when Hispanic is interacted with percent Hispanic or when Asian/PI is interacted with percent Asian. This suggests that the protective effect of living in a neighborhood with a higher percentage of one's own racial/ethnic group is largely unique to Black mothers. Although the interaction between "other' and "percent other" is also significant, it is not clear what this means without further investigation. It is possible that this effect is related to AI/AN mothers, but caution should be used when interpreting this result.

Model 6 adds controls. For the most part, coefficients for race/ethnicity, racial/ethnic composition, and interactions remain about the same, but the interaction between Black and percent Black is no longer significant. This suggests that the observed difference in the effect of Black composition between Black mothers and white mothers is explainable by one or more of the control variables.

Table 3.3. Multilevel logistic regression results from interaction models predicting low birthweight

	Model 5			Model 6			Model 7			Model 8		
	OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI	
Black	2.492	1.721	3.581	2.542	1.747	3.666	2.412	1.696	3.431	2.421	1.704	3.443
% Black	1.007	0.998	1.015	1.004	0.995	1.012	1.008	1.000	1.016	1.004	0.996	1.013
Black x % Black	0.990	0.980	1.000	1.000	0.981	1.001	0.989	0.979	0.999	0.990	0.981	1.000
Hispanic	0.704	0.385	1.267	0.767	0.418	1.377						
% Hispanic	1.002	0.994	1.010	1.000	0.992	1.008						
Hispanic x % Hispanic	1.007	0.994	1.020	1.006	0.993	1.019						
Asian/PI	0.937	0.426	1.979	0.951	0.414	2.111						
% Asian	0.994	0.979	1.009	0.994	0.978	1.009						
Asian x % Asian	0.995	0.967	1.024	1.001	0.972	1.029						
Other	5.085	2.111	11.575	5.865	2.591	13.558						
% Other	1.037	1.004	1.073	1.035	1.001	1.067						
Other x % Other	0.921	0.832	1.001	0.925	0.841	0.999						
Controls												
Age				0.995	0.974	1.016				1.000	0.980	1.020
Age^2				1.001	0.999	1.004				1.001	0.998	1.004
HS Diploma				0.743	0.524	1.066				0.730	0.510	1.046
Bachelors+				0.647	0.431	0.996				0.619	0.414	0.936
US Born				0.899	0.551	1.461				0.901	0.591	1.398
Twins				38.629	26.496	56.599				36.771	25.628	53.452
Triplets+				51.987	2.145	2375.587				56.818	2.319	2664.522
Median HH Income (logged)				0.875	0.672	1.147				0.830	0.647	1.065
Intercept	0.030	0.023	0.038	0.068	0.020	0.230	0.034	0.027	0.042	0.095	0.031	0.285
LOOIC	5276.1			4917.6			5285.7			4925.9		

Notes: n=9,652 births, OR=odds ratio, 95% CI=95% credible interval, LOOIC=leave-one-out cross-validation information criterion. Reference category for race/ethnicity is white for Models 5 and 6 and non-Black for Models 7 and 8. Reference categories for control variables are less than high school for educational attainment, foreign born for nativity, and singleton for multiple gestation.

To further explore the protective effect that Black mothers experience when living in a higher percentage Black neighborhood, Model 7 includes an interaction between individual-level Black racial identity and percent Black composition without including any of the other racial/ethnic identities or compositions. The main effects for Black and percent Black and the interaction effect are about the same as they were in Model 5 when the other racial/ethnic groups were included. This suggests that Black mothers experience a protective effect when living in a higher percentage Black neighborhood compared to white women and compared to non-Black women in general.

Model 8 adds control variables. For the most part, the magnitude of the effects remains about the same, but unlike when controls were added in Model 6, the interaction effect remains statistically significant. This is interesting and suggests that while the observed difference in the effect of percent Black between Black and white mothers is driven by one or more of the control variables, the observed difference between Black and non-Black mothers is not accounted for by these variables.

Figure 3.1 shows the differential effect of percent Black composition for Black and non-Black mothers using results from Model 7. Here we see that among neighborhoods with a small percentage of Black population, Black mothers are predicted to have a much higher risk of LBW than white mothers. However, as the percent of Black population increases, Black mothers experience a protective effect, while non-Black mothers experience greater risk of LBW. Eventually at around 80% Black population, predicted LBW for Black mothers actually becomes lower than that of non-Black mothers.

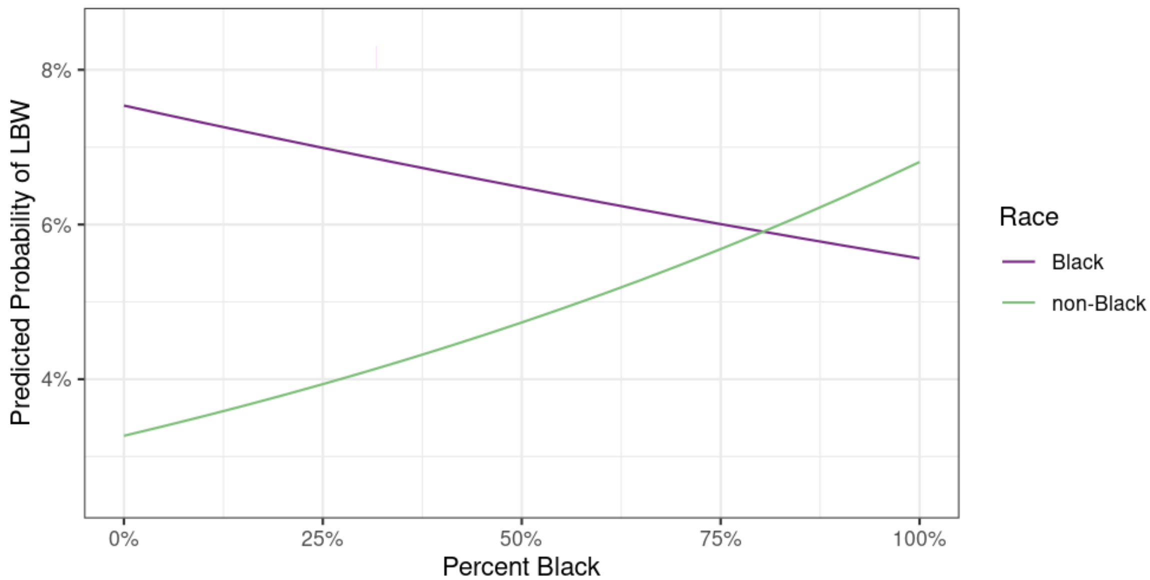

Figure 3.1. Predicted probability of LBW for Black and non-Black mothers by census tract percent Black population. Probabilities were calculated using results from Model 7.

Discussion

In this analysis I used multilevel logistic regression to address two research questions. First, I examined how LBW inequalities are shaped by individual-level race/ethnicity and neighborhood-level racial/ethnic composition, separately, additively, and interactively. Second, I looked at whether higher neighborhood racial/ethnic composition corresponding to one's own racial/ethnic identity provides a protective effect for risk of LBW.

Results from the first part of the analysis showed that Black racial identity at the individual level is associated with a higher risk of LBW, while Hispanic and Asian/PI identities are not. Further living in a census tract with a higher percentage of Black population is associated with a higher risk of LBW, while a higher percentage of Hispanic and Asian population is not associated with higher risk. However, when individual-level race/ethnicity and census tract-level racial/ethnic composition were added to the model together, the effect of individual-level Black identity remained large in magnitude and statistically significant, while the effect of census tract-level Black racial composition was no longer significant. This suggests that the observed effect of percent Black on LBW risk is driven by an accumulation of individual-level risk.

In the second part of the analysis, findings indicated that specifically for Black mothers there is a protective effect associated with living in a neighborhood with a higher percentage of one's own racial identity. This effect holds true whether comparing the effect for Black mothers and white mothers or comparing the effect for Black mothers and non-Black mothers. For white or for non-Black mothers, living in a neighborhood with a higher percentage of Black population is associated with a greater risk of LBW. However, for Black mothers, living in a neighborhood with a higher percentage of Black population is associated with a slight decrease in risk of LBW. It is not entirely clear why this is the case but given that prior research has shown that neighborhood social relationships and engagement were associated with a lower risk of LBW (Morenoff 2003), it could be that Black mothers may experience greater social support in higher Black neighborhoods which could lead to lower risk of LBW. Further, it is possible that Black mothers in neighborhoods with a larger Black population experience less stress from interpersonal racism than what they may encounter in neighborhoods with fewer Black people. Future research should further explore factors that may contribute to this protective effect.

Interestingly, the interaction effect between Black racial identity and percent Black composition was no longer significant after adding the control variables when comparing Black mothers to white mothers but it stayed significant when comparing Black mothers to non-Black mothers. It is not entirely clear why this is the case, but it could indicate a relationship between racial identity, racial composition, and SES. If white individuals living in higher percent Black neighborhoods are more likely to have low SES or if they are more likely to live in higher SES Black neighborhoods, then it would make sense that when comparing Black to white mothers the interaction effect disappeared when educational attainment and median household income were controlled for. However, if this relationship with race, racial composition, and SES does not hold true for non-white individuals, that might explain why the interaction effect remained significant when comparing Black to non-Black mothers. Further research is needed to explore this interesting dynamic.

In both parts of the analysis, a statistically significant effect for "other" racial identity was observed. In the first part, the effect of individual-level "other" racial identity was large in magnitude and statistically significant. In the second part, there was significant interaction effect between "other" racial identity and "percent other". It is unclear what these results mean since "other" encompasses multiple racial/ethnic identities, but this effect is likely driven at least in part by AI/AN identity being included in this category. Future research should investigate how AI/AN racial identity and composition affect LBW risk, both additively and interactively.

Overall, these findings are consistent with previous research that has found that Black women in particular have disproportionately high risk of LBW, even when controlling for factors like socioeconomic status (Lu and Halfon 2003). This highlights the need for continued funding and expansion of programs and interventions that support high risk individuals and communities.

Further, these results contribute to the existing literature by providing insight into how individuals' health risks are influenced simultaneously by their social identities and their neighborhood contexts and demonstrate the importance of multilevel thinking. Not only is it important to look at multiple levels to avoid ecological fallacy and/or individualistic fallacy, but it is important to consider how multiple levels interact to influence health outcomes. The results of this analysis revealed that patterning of LBW by neighborhood-level racial/ethnic composition and by individual-level race/ethnicity was largely the same. However, looking at the interaction between individual-level race/ethnicity and neighborhood-level racial/ethnic composition revealed important patterning that would have been missed with a single level approach.

Despite these contributions, this analysis is not without limitations. One important limitation of this study is the gaps of time between waves of data collection for the Add Health sample. I chose to use data from the wave of data collection prior to each birth, but it's possible the values of some variables could have changed from the time of data collection to the time of the birth, particularly for census tract racial/ethnic composition. Repeating this analysis with another dataset where information was collected at or near the time of birth would strengthen these findings.

CHAPTER IV

INTERSECTIONAL INEQUALITIES IN THE EFFECT OF NEIGHBORHOOD MEDIAN HOUSEHOLD INCOME ON LOW BIRTHWEIGHT

Introduction

Birthweight is a commonly used metric of infant health. Babies born low birthweight (LBW), or less than 2500 grams (about 5.5 lbs.), are at an increased risk of infant mortality (Ely and Driscoll 2021; Pusdekar et al. 2020), as well as several adverse health and developmental outcomes in childhood and as adults, including asthma, hypertension, coronary heart disease, and diabetes (Barker et al. 2002; Choi and Martinson 2018; Hassan et al. 2021; Nepomnyaschy and Reichman 2006; Whincup et al. 2018). Further, LBW is associated with lower socioeconomic attainment later in life (Bilgin et al. 2018) and an increased sensitivity to environmental exposures (Faust et al. 2017).

Risk of LBW is patterned by race/ethnicity (Alhusen et al. 2016; Almeida et al. 2018; Lu and Halfon 2003; Womack 2018), socioeconomic status (SES) (Blumenshine et al. 2010; Finch 2003; Jansen et al. 2008; Ramraj et al. 2020), and neighborhood context (Legerski and Thayn 2013; Matoba and Collins 2017; Morenoff 2003). However, studies rarely look at how the interaction between these social determinants shape LBW risks. Further, studies typically focus on individual-level or neighborhood-level predictors, without considering how neighborhood contexts may affect social groups in different ways.

To address these gaps in the literature, I utilize data on 10,531 births that occurred between 1990 and 2018. Data comes from the National Longitudinal Study of Adolescent to Adult Health (Add Health) (Harris et al. 2019). I employ an innovative intersectional MAIHDA approach to address two main research questions. First, how are LBW inequalities patterned intersectionally by race/ethnicity and SES? Second, how does the effect of census tract median household income on LBW vary across intersectional social strata?

Findings show that LBW risk varies considerably across social strata and that the effect of neighborhood median household income is not uniform across strata. Further, Black women experience particularly high risk of LBW, even among women with high educational attainment and who live in advantaged neighborhoods.

The Social Determinants of Low Birthweight

Race and socioeconomic status (SES) have been theorized as fundamental causes of inequalities in health outcomes because they affect exposure to risk factors that can affect health as well as access to resources to minimize the effects of disease if it does occur (Link and Phelan 1995). When thinking about birthweight, race and SES can operate as fundamental causes of LBW in several ways, including stress (Turner 2010; Wadhwa et al. 2011), exposure to hazardous environments (Rich et al. 2015), and access to quality healthcare (Shi 2004). These risks occur at both the individual and neighborhood level.

Krieger's ecosocial theory (Krieger 2001) further highlights the importance of considering how individual- and neighborhood-level social determinants affect health outcomes like LBW. Krieger argues that the material and social world in which we live becomes biologically incorporated, or embodied, throughout our lifetime (Krieger 2011). This embodiment can occur through many pathways at multiple levels. Specific to pregnancy and LBW, access to quality prenatal care, exposure to environmental toxins, and stress are just some of the ways that the social world can become embodied and affect adverse birth outcomes (Krieger et al. 2020).

Inequalities in LBW are patterned by race/ethnicity (Alhusen et al. 2016; Almeida et al. 2018; Womack 2018) and SES (Blumenshine et al. 2010; Ramraj et al. 2020). Black women in particular have been shown to have a disproportionately high risk of LBW compared to other racial/ethnic groups (Lu and Halfon 2003). Further, higher rates of low birthweight have been observed among women with less education (Jansen et al. 2008) and with lower household incomes (Finch 2003).

Racial/ethnic inequalities in LBW have been theorized to occur when exposure to discrimination, environmental hazards, and other stressors cause premature "weathering" among racially/ethnically minoritized mothers (Geronimus 1996). The weathering hypothesis suggests that racially/ethnically minoritized individuals experience excess chronic activation of psychosocial stress pathways that lead to the embodiment of these experiences in the form of premature biological aging (Geronimus et al. 2006). In a key study by Geronimus (1996), Black mothers are shown to experience a weathering effect that leads not only to higher risk of LBW at all ages compared to white mothers, but also to a different shaped relationship between age and LBW risk. The lowest risk of LBW occurs at a younger age for Black mothers and there is a less pronounced LBW risk associated with teen pregnancy.

The relationship between risk of LBW and other racial/ethnic identities is less clear, perhaps because categories such as "Asian" and "Hispanic" encompass several diverse subgroups. One such distinction within these categories that may play a role in birth outcomes is nativity or immigration status. On the one hand, being foreign-born could result in poor birth outcomes due to social, political, economic, and legal vulnerability, particularly among asylum seekers and refugees (Heslehurst et al. 2018). However, research has sometimes shown a "healthy immigrant' effect in which immigrants experience better health outcomes than their non-immigrant counterparts and in which health outcomes worsen the longer immigrants reside in the U.S., possibly due to less exposure to U.S. racial hierarchies and acculturation (Andrasfay and Goldman 2020; Ghazal Read and Emerson 2005). These patterns are also observed in research on birth outcomes, including birthweight (Acevedo-Garcia et al. 2007; Andrasfay and Goldman 2020; Heslehurst et al. 2018).

SES may influence LBW through several mechanisms including access to information and resources (Shi 2004) and stress (Turner 2010; Wadhwa et al. 2011). Koning and Ehrenthal (Koning and Ehrenthal 2019) identify "stressor landscapes" that consist of differing patterns of stressful maternal life events preceding birth. They find that low income and racial minority women are more likely to experience toxic stressor landscapes and that mothers in toxic stressor landscapes are at greater risk of experiencing preterm birth and low birthweight.

While many factors that affect LBW through mechanisms such as stress, exposure to environmental harms, and access to resources occur at the individual level, it is also important to consider how these are affected at the neighborhood level. For instance, Shi (2004) found that having more primary health care providers in an area was associated with better birthweight outcomes, especially in areas with high levels of social disparities. Further, Rich et al. (2015) looked at low birthweight rates among babies born to women in Beijing who were pregnant during the 2008 Olympics, which was a time when air pollution was significantly lower than normal. They found that babies whose 8th month of gestation occurred during the 2008 Olympics were on average 23 grams larger than babies whose 8th month of gestation occurred during the same calendar dates the year before or the year after. Additionally, Morenoff (2003) found that neighborhood contexts influence birthweight, with stress and adaptation mechanisms being the best neighborhood-level predictors of low birthweight. Despite ample work that looks at LBW at either the individual *or* neighborhood level, insufficient work has been done that considers the role of individual-level and neighborhood-level factors on LBW *simultaneously*.

It is important to consider not only how social determinants affect risk of LBW independently, but also how they interact to produce inequalities in LBW outcomes (Nieves et al. 2023). Intersectionality theory originates with Black feminist scholars (Collins 1990; Crenshaw 1990) and conceptualizes axes of marginalization such as racism, sexism, and socioeconomic inequality as interlocking systems of oppression that cannot be understood individually. Further, intersectional scholars have argued that it is important to consider the role of contextual processes, such as those at the neighborhood level, in producing intersectionally patterned experiences and outcomes (Choo and Ferree 2010; Crenshaw 1990; May 2015). A few studies have incorporated context into intersectional analyses examining low birthweight inequalities, but these typically focus on a specific geographic location, such as De Maio et al.'s (2017) look at the relationship between racial/ethnic minority segregation and low birthweight in Chicago and Toronto, or a specific population, such as Coley and Nichols' (Coley and Nichols 2016) research on adolescent mothers.

Intersectional scholarship often falls into one of three approaches: the *anticategorical* approach which centers on deconstructing social categorizations, the *intracategorical* approach which seeks to highlight the experiences of people at the intersections of multiple systems of oppression, and the *intercategorical* approach which focuses on estimating inequalities by considering the interactions between axes of marginalization (McCall 2005). I utilize an *intercategorical* approach to consider how race/ethnicity, educational attainment, and neighborhood median household income interact to affect LBW.

Research Aims

In this analysis, I employ an intersectional framework to look at how LBW rates are patterned intersectionally by race/ethnicity and socioeconomic status. Further, I consider the role of neighborhood context by examining how the relationship between neighborhood median household income and LBW varies across different intersectional groups.

To do this, I utilize intersectional Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA) (Evans, Williams, Onnela, and S. V. Subramanian 2018; Merlo 2018). There are several methodological advantages of intersectional MAIHDA over conventional interaction models (Bell, Holman, and Jones 2019; Evans 2019a; Evans, Williams, Onnela, and S. V. Subramanian 2018; Mahendran, Lizotte, and Bauer 2022). To look at how the interaction between individual- and neighborhood-level variables affect LBW, I utilize an innovative random effects MAIHDA approach. Recently, Evans et al. (2023) demonstrated the use of this approach to look at the intersectional patterning of the birthweight gap between singleton and twin births. In their analysis, they included random coefficients for a categorical variable (singleton vs. twins). Similarly, I utilize a random effects MAIHDA model, but I demonstrate the use of random slopes for a continuous variable (census tract median household income).

Data and Methods

Data

Data comes from the restricted-use National Longitudinal Study of Adolescent to Adult Health (Add Health) (Harris et al. 2019). Add Health is a large longitudinal survey of a nationally representative sample of U.S. adolescents who were in grades 7-12 during the first wave of data collection (1994-95). Respondents have been followed for five waves of data collection, with the most recent occurring in 2016-18 when respondents were aged 33-43.

In Wave 5 respondents were asked to report retrospective information about births that had occurred for them and their partners. I utilize this data along with demographic data from all waves of Add Health. I started with all births reported by female respondents that had data for birthweight (n=11,122). I excluded any births that were missing data for birth date (n=552) and any for which the respondent's race was indicated as "other" (n=39). This resulted in an analytic sample of 10,531 births that occurred between 1990 and 2018.

I was unable to determine mother's highest educational attainment prior to birth for 1,129 cases (10.72% of all cases). The most common reason for this was respondents who had missed one or two waves of data collection after the initial wave but then returned at a later wave. In these instances, information is available about births that had occurred during the gap in data collection, but detailed educational information was not available to determine what level of education the respondent had attained prior to the birth. Further, 90 cases (0.85% of all cases) were missing data on census tract median household income. Rather than drop cases that were missing information on educational attainment or median household income from the analysis, I chose to impute these missing values using multiple imputation. I used the mice package in RStudio (van Buuren and Groothuis-Oudshoorn 2011) to impute 5 datasets.

Dependent Variable

When asked about births, Add Health respondents were asked to report the birthweight of the baby. When available, I used this to code *low birthweight* as 1=yes if the baby weighed less than 5.5 pounds or 0=no if the baby weighed 5.5 pounds or more. If respondents reported that they did not know the birthweight of the baby, they were asked a follow up question of whether the baby was more or less than 5.5 pounds. When applicable, I utilized this to determine whether the baby was LBW.

Social Strata

Race/ethnicity comes from Wave 5 except for 32 cases that were missing this information for Wave 5. Wave 1 race/ethnicity data was used instead for these cases. If Add Health respondents indicated they belonged to more than one racial/ethnic category, they were asked to choose the one that they most strongly identified with. I utilized these responses when applicable. Five race/ethnicity categories were constructed: 1=white, 2=Black, 3=Hispanic, 4=Asian, and 5=American Indian/Alaska Native or Pacific Islander (AI/AN/PI).

Education is a measure of the highest level of education that the mother had achieved prior to the date of the birth. Three categories of education were constructed: 1=less than a high school (HS) diploma or equivalent, 2=high school diploma or equivalent (including GED), and 3=bachelor's degree or higher.

Neighborhood Context

Neighborhood *median household income* is a measure of the median household income (in $1,000s) for the census tract in which the mother was residing at the wave of data collection prior to the date of birth. All median household income values were adjusted to be equivalent to 2008 dollars. I used a logged version of median household income in the models and centered the variable at the mean.

Controls

To account for other factors that have been shown to have a relationship with birthweight, I include controls for maternal age, maternal nativity status, and multiple gestation. Controlling for these things removes the effect of potential compositional differences in these variables. For instance, if twins are more common in some social strata, this may elevate the predicted risk of LBW for those strata given that twins' risk of LBW is 10.3 times greater than singletons' (Luke and Keith 1992). This allows us to see if observed inequalities between social strata are driven by these variables or if the inequalities persist even after accounting for them.

Maternal age is calculated by subtracting the birthdate of the baby from the mother's birthdate. I include age and age-squared in the models to account for the non-linear relationship between age and LBW (Evans et al. 2023; Geronimus 1996). In the models, I center age at the mean.

U.S. born is a measure of maternal nativity status and is coded as 1=yes if the mother was born in the U.S. and 0=no if the mother was born somewhere else.

It is important to control for *multiple gestation births*, as it is well established that compared to singleton births, multiple births are at a higher risk for several adverse birth outcomes (Kalikkot Thekkeveedu et al. 2021), including LBW (Luke and Keith 1992). Births are coded as singleton, twins, or triplets+.

Social Strata IDs

Social strata were constructed using race/ethnicity and educational attainment as coded above. A two-digit stratum ID code was used consisting of individual race/ethnicity in the first position and individual educational attainment in the second position. For example, a stratum ID code of 23 would indicate an individual who is Black and has a bachelor's degree or higher. A summary of stratum ID codes and sample size for each stratum is shown in Table 4.1.

Table 4.1. Stratum ID codes and sample sizes

Stratum ID	First Position: Race/ethnicity	Second Position: Educational attainment	Mean Sample Size (*n*)
11	1=White	1=Less than HS	660
12	1=White	2=High school diploma or GED	3,501
13	1=White	3=Bachelor's degree or higher	2,184
21	2=Black	1=Less than HS	421
22	2=Black	2=High school diploma or GED	1,424
23	2=Black	3=Bachelor's degree or higher	453
31	3=Hispanic	1=Less than HS	247
32	3=Hispanic	2=High school diploma or GED	817
33	3=Hispanic	3=Bachelor's degree or higher	265
41	4=Asian	1=Less than HS	17
42	4=Asian	2=High school diploma or GED	193
43	4=Asian	3=Bachelor's degree or higher	186
51	5=AI/AN/PI	1=Less than HS	44
52	5=AI/AN/PI	2=High school diploma or GED	111
53	5=AI/AN/PI	3=Bachelor's degree or higher	10

Note: Stratum sample sizes vary slightly across five imputed datasets so reported values are the mean sample sizes for the five datasets.

Methodological Approach

I utilize an intersectional multilevel approach—Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA)—that allows for individuals to be nested within intersectional social positions (Evans, Williams, Onnela, and S. V. Subramanian 2018; Merlo 2018). Traditional quantitative intersectional analyses have typically used interaction terms in single-level regression models to look at intersectional relationships. The MAIHDA approach has several theoretical and practical advantages over the conventional approach, including easier interpretability even with a relatively large number of interactions and better handling of small sample sizes in some strata (Bell et al. 2019; Evans 2019a; Evans, Williams, Onnela, and S. V. Subramanian 2018; Mahendran et al. 2022).

My analysis consists of two main parts. I first utilize a traditional logistic MAIHDA approach to look at the intersectional patterning of LBW across individual-level social strata. I then utilize a logistic *random effects* MAIHDA approach to look at how the effect of neighborhood median household income on LBW varies across social strata.

LBW Inequalities

In the first part of the analysis, I assess the intersectional patterning of LBW across individual-level social strata and look at how much of the variation in LBW is occurring due to interactive, rather than additive, effects. I use traditional logistic MAIHDA models in which individuals are nested in intersectional social strata consisting of racial/ethnic identity and educational attainment.

The general equation for the model is:

$$lbw_{ij} \sim Bernoulli(\pi_{ij})$$

$$log \frac{\pi_{ij}}{(1-\pi_{ij})} = \beta_0 + \beta_\alpha \gamma_j + \mu_{0j}$$

$$\mu_{0j} \sim N\left[0, \sigma^2_{\mu_0}\right]$$

$$Var\left(lbw_{ij} \middle| \pi_{ij}\right) = \pi_{ij}(1-\pi_{ij})$$

where π_{ij} is the probability of birth *i* in in stratum *j* being LBW, γ_j is a vector of additive main effects for maternal race/ethnicity and educational attainment, and β_α is a vector of associated parameter values. μ_{0j} is the stratum-level residual difference in predicted LBW risk. Stratum-level residuals are normally distributed with mean 0 and variance $\sigma^2_{\mu_0}$.

This part of the analysis includes three logistic MAIHDA models:

Model 1 is a null model that only includes the intercept (β_0) and the stratum level random effects (μ_{0j}). The amount of inequality in predicted low birthweight between strata is captured by $\sigma^2_{\mu_0}$. Another measure of between-stratum variance is the Variance Partition Coefficient (VPC). The VPC is a measure of the proportion of the total variance that is attributable to the stratum level. In logistic models, the individual-level variance can be estimated using the latent variable approach (Goldstein, Browne, and Rasbash 2002) in which $\sigma^2_{e_0} = \frac{\pi^2}{3} = 3.29$.

The equation for the VPC is:

$$VPC = \frac{Between\ Stratum\ Variance}{Total\ Variance} * 100\% = \frac{\sigma^2_{\mu_0}}{\sigma^2_{\mu_0} + \sigma^2_{e_0}} * 100\%$$

Model 2 adds the additive main effects for race/ethnicity and educational attainment categories ($\beta_\alpha \gamma_j$).

Model 3 includes the additive main effects for race/ethnicity and educational attainment and also adds controls for maternal age, nativity status, and multiple gestation.

An additional statistic of interest in MAIHDA analysis is the Proportional Change in Variance (PCV). The PCV indicates the amount of between-stratum variance that is "explained" by adding the fixed parameters to the model. The PCV for Models 2 and 3 is calculated as:

$$PCV = \left[\frac{\sigma^2_{\mu_0,Model1A} - \sigma^2_{\mu_0,Model1B,1C}}{\sigma^2_{\mu_0,Model1A}}\right] * 100\%$$

The PCV for Model 2 is a measure of the between-strata inequality that is explained by additive main effects and the PCV for Model 3 is a measure of the between-strata inequality that is explained by the additive main effects and the control variables.

Adding Neighborhood Context

In the second part of the analysis, I look at the effect of neighborhood median household income on LBW and consider how this effect varies across social strata. I start with a traditional logistic MAIHDA model to consider the overall effect of median household income. The general equation for this model is the same as above with an added fixed effect for census tract median household income ($\beta_1(CTinc_{ij})$).

I then consider how the effect varies across social strata by utilizing a logistic *random effects* MAIHDA approach (Evans et al. 2023) in which census tract median household income is added as a random slope. Adding census tract median household income as a random slope allows the predicted effect of census tract median household income to vary by stratum j. In other words, the model allows for the relationship (slope) between neighborhood income and

LBW to take a unique value in each intersectional social stratum. The general form of the equation for this model is:

$$log\frac{\pi_{ij}}{(1-\pi_{ij})} = \beta_0 + \beta_1(CTinc_{ij}) + \beta_{\propto}\gamma_j + \mu_{0j} + \mu_{1j}(CTinc_{ij})$$

$$\begin{bmatrix}\mu_{0j}\\ \mu_{1j}\end{bmatrix} \sim N\left(0, \begin{bmatrix}\sigma^2_{\mu_0} & \square \\ \sigma^2_{\mu_0\mu_1} & \sigma^2_{\mu_1}\end{bmatrix}\right)$$

with a similar interpretation as above, except β_1 represents the overall effect of census tract median household income across all strata and μ_{1j} indicates how much this effect differs from β_1 for stratum j. In other words, the effect of census tract median household income for stratum j (β_{1j}) is given by $\beta_{1j} = \beta_1 + \mu_{1j}$. $\sigma^2_{\mu_0}$ is the between-stratum variance in the probability of LBW for an individual living in a census tract with a median household income of \$43,380, $\sigma^2_{\mu_1}$ is the between-stratum variance in the change of predicted probability of LBW associated with each \$1,000 increase in median household income, and $\sigma^2_{\mu_0\mu_1}$ is the covariance between μ_{0j} and μ_{1j}.

This part of the analysis includes four MAIHDA models:

<u>Model 4</u> is a traditional logistic MAIHDA model and includes census tract median household income to the model as a fixed effect. This provides a predicted effect of census tract median household income on low birthweight, but the effect is assumed to be the same in all strata.

<u>Model 5</u> is a logistic random effects MAIHDA model that includes census tract median household income but treats the variable as a random coefficient. This model allows for the relationship between census tract median household income and LBW to be unique for every stratum.

Model 6 treats median household income as a fixed effect (like Model 4) and includes all additive main effects and control variables.

Model 7 treats median household income as a random coefficient (like Model 5) and includes all additive main effects and control variables.

All models were fit in RStudio using the brm_multiple command from the brms library (Bürkner 2017). brm_multiple is well-suited for using imputed data as it allows for multiple datasets to be used in the model. It runs the model for each imputed dataset then pools the results. Following the convention used in previous MAIHDA analyses, models have a burn-in of 5,000 iterations with a total length of 50,000 iterations (with thinning every 50 iterations).

Results

Descriptive statistics are shown in Table 4.2. In the sample, 8.70% of the births were considered LBW (less than 5.5 lbs.) About 60% of births were to white mothers, about 20% were to Black mothers, about 13% were to Hispanic mothers, about 4% were to Asian mothers, and about 1.5% were to AI/AN/PI mothers. Just over half of the births were to mothers whose highest educational attainment was a HS diploma or GED, a little over a quarter were to mothers with a bachelor's degree or higher, and just under 10% were to mothers with less than a HS diploma. The mean census tract median household income in which mothers resided during the wave of data collection prior to the birth was about $48,000. Census tract median household income varied considerably, with the lowest being just $7,280 and the highest being $190,900. The mean maternal age was 27.73 years. About 91% of births were to U.S. born mothers and about 96% were singleton births.

Table 4.2. Descriptive statistics of sample (*n*=10,531 births)

Dependent Variable	*n*	%				*n* Missing	% Missing
LBW						0	0
Yes	916	8.70					
No	9,615	91.30					
Social Strata Dimensions							
Race/Ethnicity						0	0
White	6,345	60.25					
Black	2,297	21.81					
Hispanic	1,328	12.61					
Asian	396	3.76					
AI/AN/PI	165	1.57					
Educational Attainment						1,129	10.72
Less than HS	990	9.40					
HS Diploma or GED	5,407	51.34					
Bachelor's Degree or Higher	3,005	28.53					
Neighborhood Context	Mean	SD	Median	Min	Max		
CT Median Household Income (in $1,000s)	47.95	20.97	45.35	7.28	190.90	90	0.85
Controls							
Maternal Age	27.23	5.56	27.33	13.50	41.50	0	0
	n	%					
U.S. Born						308	2.92
Yes	9,593	91.09					
No	630	5.98					
Multiple Gestation						18	0.17
Singleton	10,155	96.43					
Twins	344	3.27					
Triplets+	14	0.13					

LBW Inequalities Across Social Strata

Table 4.3 shows results from the first set of MAIHDA models that consider how LBW inequalities are patterned intersectionally by race/ethnicity and SES. The VPC in Model 1, the null model, indicates that 2.16% of the variation in LBW is attributable to the stratum level. This indicates that there is a small, but notable, amount of inequality in LBW between strata. Perhaps unsurprisingly, there is a large amount of within-stratum variance, likely due to the myriad factors that contribute to LBW.

Table 4.3. Logistic MAIHDA results

	Model 1			Model 2			Model 3		
	OR	95% CI		OR	95% CI		OR	95% CI	
Intercept	0.104	0.086	0.124	0.096	0.073	0.127	0.084	0.053	0.133
Race/Ethnicity									
White (Ref)				-	-	-	-	-	-
Black				1.709	1.292	2.250	1.833	1.377	2.424
Hispanic				1.099	0.805	1.467	1.118	0.807	1.543
Asian				1.088	0.696	1.685	1.201	0.722	1.976
PI/AI/AN				1.416	0.781	2.392	1.664	0.891	2.957
Educational Attainment									
< HS (Ref)				-	-	-	-	-	-
HS Diploma				0.814	0.616	1.095	0.762	0.557	1.056
Bachelor's +				0.838	0.608	1.143	0.684	0.471	1.004
Controls									
Age							0.995	0.979	1.010
Age^2							1.001	0.999	1.003
U.S. Born							0.918	0.650	1.305
Twins							19.289	15.328	24.527
Triplets+							393.740	53.473	8804.604
Random Effects	Est			Est			Est		
Strata variance ($\sigma^2_{\mu_0}$)	0.074			0.009			0.011		
VPC (%)	2.213			0.280			0.329		
PCV (%) (compared to null model)				87.605			85.40		

Notes: n=10,531, OR=odds ratio, 95% CI=95% credible interval, VPC=variance partition coefficient, PCV=proportional change in variance.

Model 2 includes the additive main effects for the strata variables. In this model, we see that purely from an additive perspective, the effects of race/ethnicity and educational attainment are consistent with what we would expect—women with non-white racial/ethnic identities, particularly Black women, have higher odds of LBW births and having a high school or college education is associated with lower odds of LBW compared to having less than a high school education. The PCV for Model 2 indicates that 87.6% of the between-stratum variance is explained by the additive main effects.

Model 3 adds controls for maternal age, nativity status, and multiple gestation. In this model, the additive main effects for race/ethnicity and educational attainment are slightly larger in magnitude. Further, a gradient effect for higher educational attainment is now apparent, likely due to the relationship between educational attainment and maternal age. Interestingly, age and nativity status do not appear to have a significant relationship with LBW. This is perhaps due to the non-uniform relationship between age and LBW across racial/ethnic groups and the complex relationship between immigration status and LBW. As expected, multiple gestation has a strong relationship with LBW, with multiple births having a much higher risk of being LBW than singleton births. Interestingly, the VPC increases slightly from Model 2 to Model 3, indicating that more variation in LBW is attributable to the stratum level once the controls are added.

Figures 4.1 and 4.2 use estimates from Model 3 to show the predicted probability of LBW for each stratum. Figure 4.1 shows these values ranked from lowest to highest and Figure 4.2 shows them sorted by race/ethnicity and educational attainment. Values range from 5.34% for white mothers with a bachelor's degree or higher to 13.30% for Black mothers with less than a high school diploma.

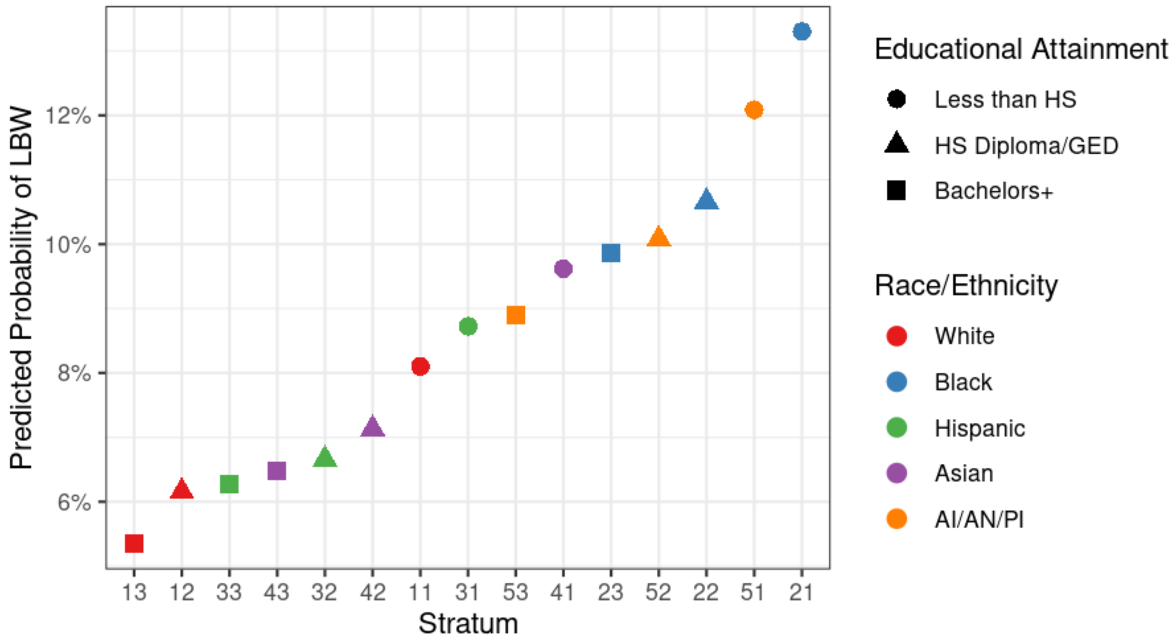

Figure 4.1. Predicted probability of low birthweight by intersectional social stratum ranked from low to high. Probabilities were calculated using results from Model 3 with all controls (maternal age, nativity status, and multiple gestation) set at the mean.

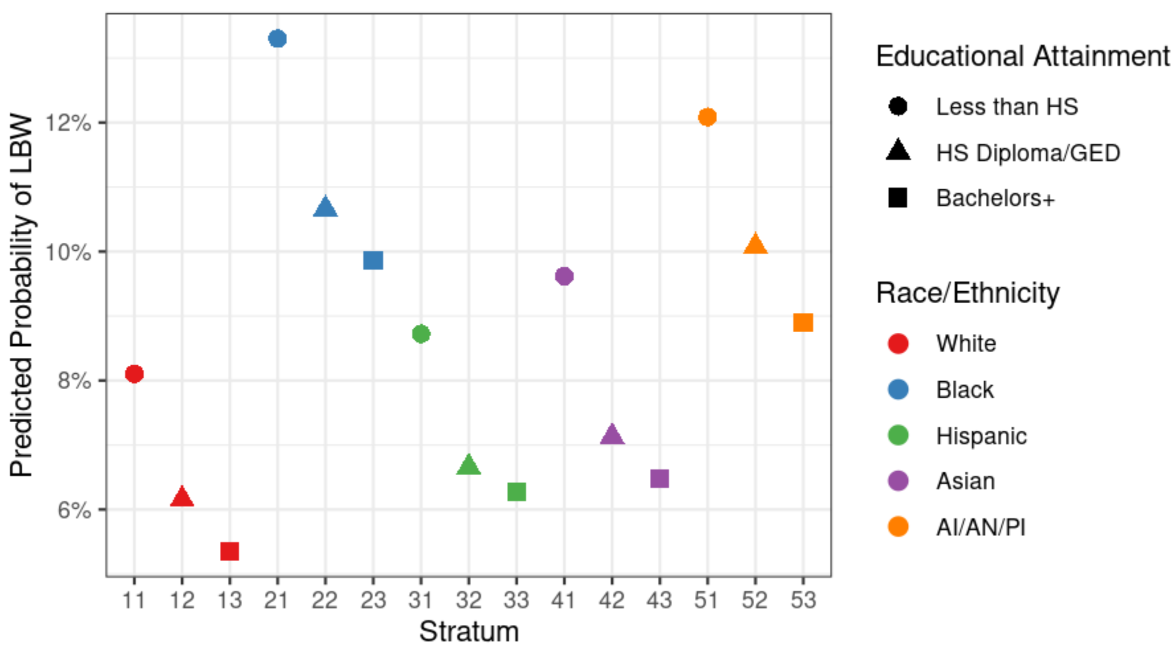

Figure 4.2. Predicted probability of low birthweight by intersectional social stratum grouped by race/ethnicity. Probabilities were calculated using results from Model 3 with all controls (maternal age, nativity status, and multiple gestation) set at the mean.

When looking at patterning by social strata, a few things stand out. First, the three strata with Black racial identity are among the highest predicted probabilities for LBW. All three Black social strata have higher predicted probabilities than all of the white, Hispanic, and Asian strata. This suggests that even among Black mothers with high educational attainment, the risk of LBW remains disproportionately high. Further, the predicted probabilities for the AI/AN/PI strata are notably high, especially among mothers with less than a bachelor's degree. Generally, lower predicted probabilities are among white, Hispanic, and Asian mothers with a high school or college degree. The strata with the very lowest predicted probabilities are specifically white mothers with a HS or college degree.

For each racial/ethnic category, there appears to be a clear decrease in predicted LBW associated with having more education. There appears to be a gradient effect where each increase in educational attainment is associated with a decrease in probability of LBW. However, this positive effect seems to be particularly strong when moving from having less than a HS education to having a HS degree.

Neighborhood Variation in LBW Inequalities

Table 4.4 shows the results from the second set of MAIHDA models that consider the effect of census tract median household income on LBW and how this effect differs across intersectional strata.

Table 4.4. Logistic random slopes MAIHDA results

	Model 4			Model 5			Model 6			Model 7		
Fixed Effects	OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI	
Intercept	0.103	0.087	0.123	0.104	0.086	0.127	0.082	0.051	0.132	0.084	0.048	0.146
Logged CT median HH income	0.885	0.746	1.042	0.897	0.754	1.077	0.885	0.737	1.064	0.895	0.742	1.101
Race/Ethnicity												
White (Ref)							-	-	-	-	-	-
Black							1.758	1.283	2.392	1.677	0.986	2.566
Hispanic							1.111	0.789	1.569	1.066	0.616	1.678
Asian							1.224	0.735	2.021	1.206	0.625	2.191
PI/AI/AN							1.663	0.865	2.891	1.534	0.641	3.016
Educational Attainment												
< HS (Ref)							-	-	-	-	-	-
HS Diploma							0.772	0.558	1.087	0.793	0.524	1.293
Bachelor's +							0.701	0.477	1.037	0.712	0.444	1.172
Controls												
Age							0.997	0.980	1.012	0.997	0.982	1.012
Age^2							1.001	0.999	1.003	1.001	0.999	1.003
U.S. Born							0.925	0.658	1.308	0.930	0.670	1.323
Twins							19.391	15.362	24.458	19.466	15.393	24.669
Triplets+							409.292	54.640	9909.806	405.475	57.759	8639.759
Random Effects	Est			Est			Est			Est		
Strata variance ($\sigma^2_{\mu_0}$)	0.064			0.065			0.012			0.051		
CT median HH income variance ($\sigma^2_{\mu_1}$)				0.007						0.004		
Covariance ($\sigma_{\mu_0\mu_1}$)				0.883						-0.357		

Notes: n=10,531, OR=odds ratio, 95% CI=95% credible interval.

Model 4 includes a *fixed effect* for logged census tract median household income. Model 6 also includes a fixed effect of logged census tract median household income but adds additive main effects for race/ethnicity and educational attainment and controls for maternal age, nativity status, and multiple gestation. Model 5 includes a *random effect* for logged census tract median household income, as does Model 7 with additive main effects and controls included. The effect of logged median household income is similar across all four models, with a 1% increase in median household income associated with about a 0.11% decrease in the odds of LBW. In other words, LBW risk decreases as neighborhood advantage increases. This is consistent with what we would expect given past research demonstrating that neighborhood disadvantage is associated with increased risk of LBW. When looking at the additive main effects and control variables in Models 6 and 7, we see similar effects as in the first part of the analysis—Black women have particularly high risk of LBW and risk of LBW decreases as educational attainment increases.

Although the overall effect of CT median household income is similar for the random slopes models as it is for the fixed effects models, Figures 4.3 and 4.4 use the random slopes estimates from Model 7 to show how the effect of CT median household income differs across social strata. Figure 4.3 shows the random slopes coefficients for each stratum. We see that higher median household income is associated with a decrease in LBW for all strata, but the coefficients range from -0.082 for AI/AN/PI mothers with a HS education to -0.148 for white mothers with a HS education. Although there does not appear to be much in the way of obvious patterning by race/ethnicity and educational attainment, one thing that stands out is the particularly strong effect of median household income for white mothers with a high school or college education. Further, all of the white social strata have larger magnitude coefficients than the overall coefficient.

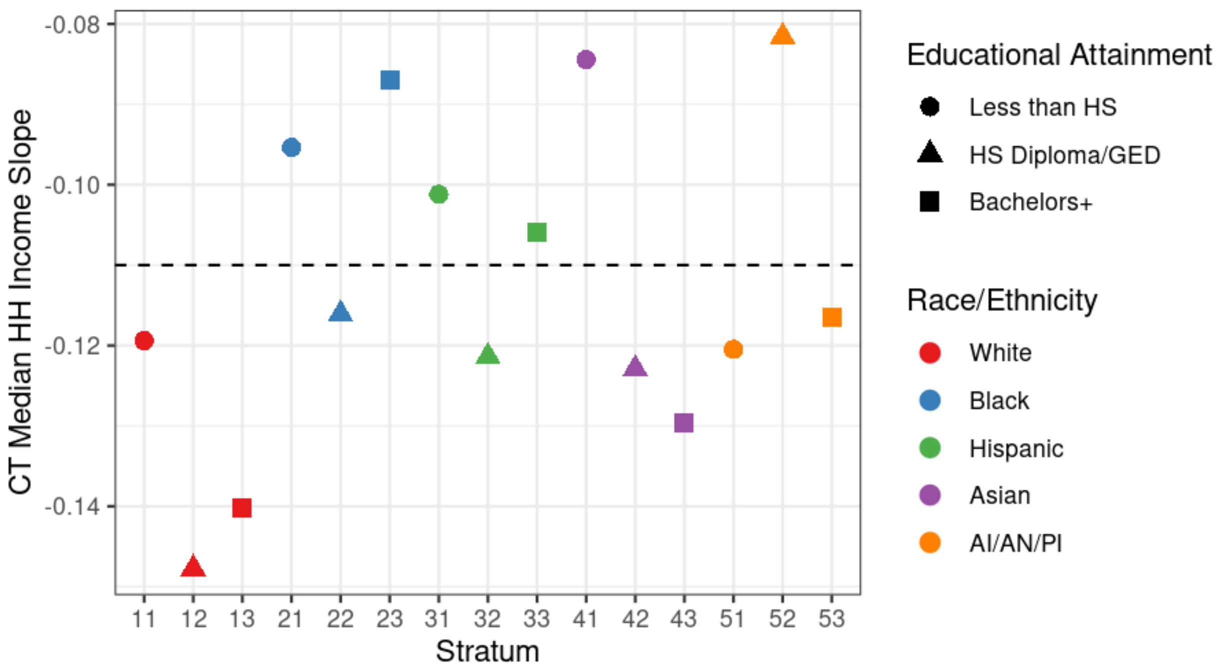

Figure 4.3. Random slopes coefficients for census tract median household income. Dotted black line indicates overall slope coefficient (-0.111). Coefficients are from Model 7. Negative slope values indicate that risk of LBW decreases as neighborhood median household income increases.

Among the Asian strata, the negative effect of median household income is much smaller in magnitude for the stratum with less than a HS diploma than it is for the other two educational attainment strata. Interestingly, there is a similar patterning between the Black and Hispanic strata where the less than HS and Bachelor's + strata have smaller magnitude coefficients than the HS diploma stratum.

Figure 4.4 shows the predicted probability of LBW for each social strata across the range of median household income. A few things stand out in this figure. First, across all values of median household income and all racial/ethnic categories, as educational attainment increases, risk of LBW decreases. Interestingly, for Asian, Hispanic, and AI/AN/PI mothers the gap between the less than a HS diploma stratum and the HS diploma stratum appears to be particularly wide, whereas for white and Black mothers, the gap between each educational attainment strata appears fairly uniform. Among Black and Hispanic mothers, the gap between those with HS diploma and those with a bachelor's degree shrinks as median household income increases, whereas this gap widens for AI/AN/AP mothers as median household income increases.

The high risk of LBW among Black mothers is once again striking and particularly apparent when looking at the disparity between Black and white mothers. Across the range of median household income, Black mothers with the highest educational attainment still experience higher predicted LBW than white mothers with the lowest educational attainment. This suggests that even with the protective effects that Black mothers appear to experience from higher educational attainment and living in more advantaged neighborhoods, they still experience much greater risk of LBW than white mothers.

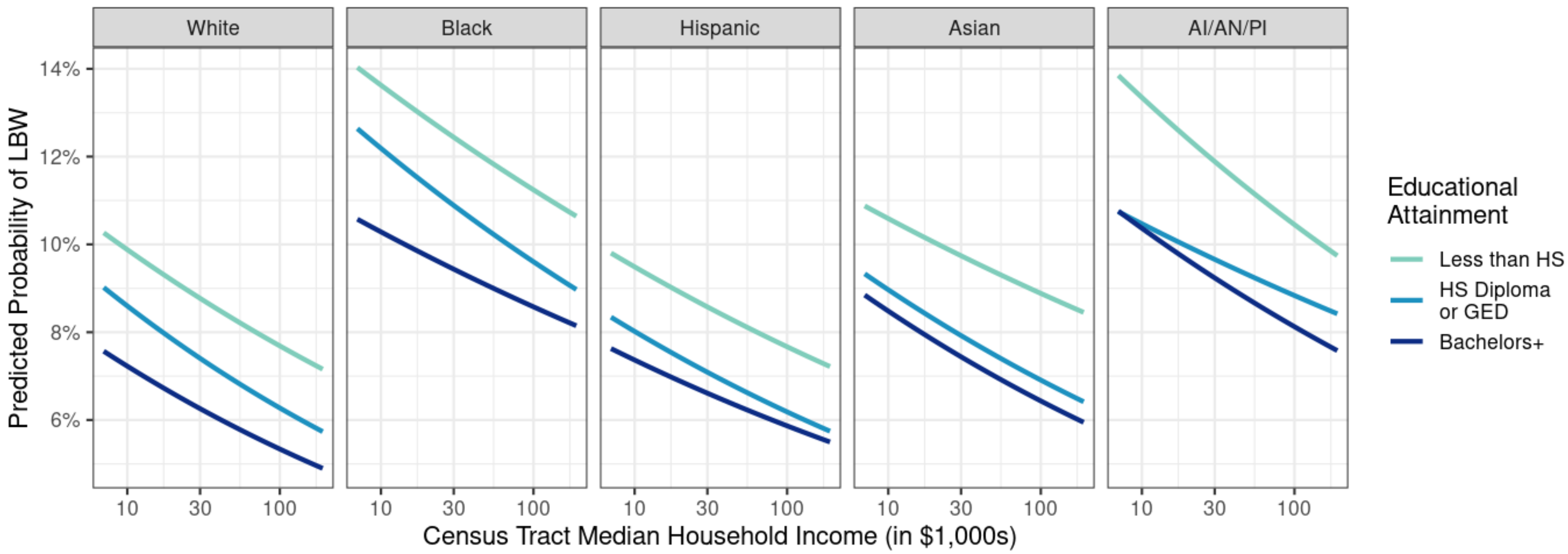

Figure 4.4. Predicted probability of low birthweight for intersectional social strata by census tract median household income. X-axis is shown with a logged scale. Probabilities were calculated using results from Model 7 with all controls (maternal age, nativity status, and multiple gestation) set at the mean.

Discussion

In this analysis I addressed two main research questions. First, I used intersectional MAIHDA models to look at how LBW is patterned across intersectional social strata consisting of race/ethnicity and educational attainment. Second, I used random slopes MAIHDA models to consider how census tract median household income affects LBW and how this effect varies across social strata.

In the first part of the analysis, I found that LBW risk varies considerably across social strata. Consistent with prior work that used a MAIHDA approach to look at LBW (Evans et al. 2023; Nieves et al. 2023), a small, but notable, amount of the variation in LBW is attributable to the stratum level. White mothers with bachelor's degrees have the lowest risk of having a LBW baby, while Black mothers with less than a high school diploma have the highest risk. Higher educational attainment is associated with lower risk of LBW for all racial/ethnic groups with a particularly strong effect when moving from less than a high school education to having a high school degree. Education itself likely plays a role in LBW risk as higher educational attainment can increase access to resources such as income, health insurance, and information. However, the observed protective effect of education likely also encompasses the effects of SES more broadly such as familial financial and social support and the ability to avoid hazardous and/or stressful environments.

Results from the second part of the analysis demonstrate that neighborhood context matters for risk of LBW. Increased neighborhood median household income is associated with a lower risk of LBW for all social strata. However, the protective effect of higher census tract median household income is not uniform across social strata. Particularly, white women with a

HS diploma or bachelor's degree appear to benefit the most from higher neighborhood median household income.

Consistent with previous research, the findings of this study show that Black mothers are at a particularly high risk of having a LBW baby (Lu and Halfon 2003). This is particularly pronounced among Black mothers with less than a HS diploma, but even Black mothers with a HS diploma or bachelor's degree still have higher predicted probability of LBW than almost all other social strata. Further, although higher neighborhood median household income appears to be associated with lower risk of LBW for Black mothers, the predicted risk of LBW remains high across the range of median household income values. This is particularly striking when comparing Black and white mothers. These findings are troublesome and suggest that even with access to higher individual and neighborhood SES, Black women still experience poor birth outcomes. It is important for policy interventions to address these disparities at the individual, neighborhood, and institutional levels.

Overall, the results of this analysis contribute to the literature by demonstrating the importance of utilizing an intersectional framework to look at health outcomes across intersecting social identities. Further, this analysis shows the value of considering individual-level and neighborhood-level social determinants simultaneously. Doing so can reveal important patterns in how inequalities are shaped that might otherwise be missed. However, this analysis is not without limitations. One important limitation of this study is the relatively large gaps of time in between waves of Add Health data collection. I opted to utilize data from the wave prior to the birth, but particularly for educational attainment and CT median household income, the values of these variables could have changed from the time of data collection to the time of the birth. Repeating this analysis with data collected at or near the time of birth would strengthen the findings. Another limitation was the small sample size for some social strata. Because of this, I was unable to include other important axes of marginalization in the social strata. Of particular interest is how maternal age, nativity status, and multiple gestation interact with race/ethnicity and SES to shape birth outcomes. Future research should consider including these variables in the social strata to see what role they play in the patterning of LBW inequalities.

CHAPTER 5

CONCLUSION

In this dissertation I sought to add to the understanding of how health inequalities are patterned and produced by examining LBW inequalities. I started by reviewing key literature that highlighted the need for the consideration of fundamental causes of health inequalities such as sexism, racism, and classism. Further, prior research has demonstrated that LBW is patterned by race/ethnicity and SES at the individual level and racial/ethnic composition at the neighborhood level. This patterning is shaped by mechanisms such as stress, social support, exposure to environmental hazards. Despite prior work on LBW inequalities, gaps still remain. My analyses added to a more complete understanding of how inequalities in LBW rates are patterned at the neighborhood level, a better understanding of how racial/ethnic inequalities in LBW are shaped at both the individual level and neighborhood level additively and interactively, and a better understanding of how LBW risk is shaped intersectionally by race/ethnicity and SES and how different intersectional groups are affected differently by neighborhood contexts.

In Chapter 2, I conducted a spatial analysis to look at the relationship between racial/ethnic composition and LBW rates across California census tracts. I then considered the role of family structure, specifically female headed households, and neighborhood deprivation in this relationship. Findings highlight neighborhood-level racial/ethnic inequalities in LBW rates. Increases in census tract proportion of Black, Hispanic, Asian, and Native population are all associated with higher LBW rates. However, these effects are not uniform across racial/ethnic composition groups and are particularly strong for percent Black and percent Native. Findings also show that a higher percentage of female headed households and increased neighborhood deprivation are both associated with higher LBW rates. Further, these variables appear to attenuate some of the effect of racial/ethnic composition on LBW rate, but this is not uniform for across racial/ethnic groups. The effect of percent Hispanic on LBW rate appears to be largely driven by percent female headed households and neighborhood deprivation, but the effects of percent Black and percent Native are only partially attenuated by the variables, and percent Asian only decreases slightly when these variables are accounted for.

Chapters 3 and 4 build on this by looking at the individual level and neighborhood level simultaneously. In Chapter 3, I completed a multilevel analysis to look at how individual-level race/ethnicity and neighborhood-level racial/ethnic composition affect LBW individually, additively, and interactively. Findings show that individual-level Black racial identity and census tract percent Black population are both associated with a higher risk of LBW, but the effect for other racial/ethnic identities is not significant. However, it appears that the effect of percent Black is driven by an accumulation of individual-level risk. Further, when looking at the interaction between individual-level race/ethnicity and neighborhood-level racial/ethnic composition, Black mothers appear to experience a protective effect from living in a neighborhood with a higher percentage of their own racial identity, while mothers of other racial/ethnic identities do not experience this effect.

Finally, in Chapter 4, I utilized an intersectional framework and innovative intersectional MAIHDA models to look at the patterning of LBW by race/ethnicity and SES. I then considered how the effect of neighborhood median household income on LBW differs across intersectional social strata. Findings indicate that LBW risk varies considerably across intersectional social strata, with white mothers with high educational attainment having the lowest risk and Black mothers with low educational attainment having the highest risk. Further, findings show that increased census tract median household income is associated with a lower risk of LBW for all social strata, but the effect is not uniform and white women with higher educational attainment benefit the most. Findings from this chapter also highlight the disproportionately high risk of LBW that Black mothers experience, even when accounting for educational attainment and neighborhood median household income.

Taken as a whole, the findings from the empirical analyses highlight several important things. First, results show that individual Black racial identity and neighborhood-level Black racial composition are both disproportionately associated with greater LBW risk. This is consistent with prior research that has shown that Black mothers in particular are disproportionately at risk of poor birth outcomes and is consistent with patterns in the U.S. in which spaces with elevated proportions of Black individuals are found to also contain multiple stressors linked to structural racism and racial segregation.

LBW inequalities observed in these analyses that are patterned by race/ethnicity and SES highlight the need for policies and programs intended to reduce these disparities. However, taking into account key theoretical perspectives on health inequalities, interventions designed to address LBW are not likely to be widely effective unless they address fundamental causes of health such as racism, SES, and segregation. Large scale policies such as universal healthcare and a livable minimum wage are key to reducing disparities in LBW. Not only will such policies directly benefit pregnant women but will lead to a more equal and safer society which in turn will promote healthier and less stressful environments for pregnant women. Further, education and training for healthcare professionals about the structural factors that affect health are needed. For instance, the health effects of structural racism are well covered in social science literature, but have not been adequately addressed in medical and scientific literature aimed at health professionals (Bailey et al. 2017). Awareness about these factors will help providers to promote health equity and to provide better care for all women. Programs like California's Black Infant Health Program which aims to improve health among Black mothers and babies by connecting Black women with vital care and support during and after pregnancy should receive continued support. Similar programs should be developed across the country that target Black women and other high-risk groups and communities.

Further, results highlight the importance of a multilevel approach when looking at health inequalities. The spatial analysis in Chapter 2 revealed important neighborhood-level patterns of LBW inequalities, but a limitation of this analysis is that we cannot draw conclusions about how these patterns operate at the individual level. Chapter 3 and 4 built on this by using a multilevel approach to consider individual-level and neighborhood-level effects simultaneously. Results from these chapters revealed important patterning that would have been missed with a single level analysis. Prior research has argued that multilevel thinking is essential to avoid ecological fallacy and/or individualistic fallacy (Subramanian et al. 2009). Avoiding these fallacies is important, but the results of the analyses in this dissertation demonstrate that the value of multilevel thinking goes beyond this, as a multilevel approach can also reveal important interactions between levels that shape inequalities. This is important not just when looking at health inequalities, but also when looking at social inequalities more broadly.

Future research should build on this work to further explore inequalities in LBW and other health outcomes. Linking the CalEnviroScreen data used in Chapter 2 with individual-level data for births in California would be an excellent way to explore how individual-level social identities and neighborhood-level contexts interact to affect LBW outcomes. This data is particularly well suited to look at the effect of environmental exposures and neighborhood deprivation.

One drawback of the Add Health data used in Chapters 3 and 4 was the large gaps of time between waves of data collection. This meant that there was some uncertainty about whether the values of some variables accurately represented the values at the time of each birth, particularly when looking at measures of individual-level and neighborhood-level SES. Repeating these analyses with data collected at or near the time of birth would likely strengthen the findings. Another limitation of the Add Health data was that the sample size did not allow for additional axes of marginalization to be included in the intersectional analysis in Chapter 4. Future work should further explore how other social identities, such as nativity status and age, intersect with race/ethnicity and SES to shape LBW risk and how these unique intersections are differentially affected by neighborhood contexts.

Further, multilevel thinking should be used to consider the role of things that affect LBW that were not included in this analysis, including social support, stress, and access to healthy foods and quality healthcare. Additionally, more investigation is needed to understand the unique protective effect that Black mothers appear to experience when living in high percent Black neighborhoods. A better understanding of this effect might be gained through qualitative methods like interviews and participant observation and could help inform ways to improve birth outcomes for all mothers.

APPENDIX A

SUPPLEMENTAL TABLE FROM CHAPTER 2

Table A1. OLS regression results predicting low birthweight rates in California census tracts (n=7619)

Variable	Model 1	Model 2	Model 3	Model 4
% Black	0.064 ***	0.052 ***	0.059 ***	0.051 ***
	(0.002)	(0.002)	(0.002)	(0.002)
% Hispanic	0.019 ***	0.012 ***	0.010 ***	0.007 ***
	(0.001)	(0.001)	(0.001)	(0.001)
% Asian	0.020 ***	0.018 ***	0.017 ***	0.016 ***
	(0.001)	(0.001)	(0.001)	(0.001)
% Native	0.106 ***	0.084 ***	0.072 ***	0.063 ***
	(0.018)	(0.018)	(0.018)	(0.018)
% FHH		0.038 ***		0.027 ***
		(0.005)		(0.005)
Neighborhood Deprivation Scale			0.271 *** (0.028)	0.219 *** (0.029)
Intercept	3.635***	3.445 ***	4.037 ***	3.824 ***
	(0.040)	(0.045)	(0.057)	(0.067)
Akaike information criterion (AIC)	26551.96	26482.04	26459.09	26427.08
Adjusted R-squared	0.232	0.239	0.241	0.244
Moran's I of residuals[a]	0.111***	0.102***	0.100***	0.096***

Notes: *** p < 0.001; ** p < 0.01; * p < 0.05. Standard errors are in parentheses.
[a]A first-order queen adjacency spatial weights matrix was used to calculate Moran's I.

APPENDIX B

SUPPLEMENTAL TABLE FROM CHAPTER 3

Table A2. Multilevel logistic regression results predicting low birthweight

	Model 9			Model 10		
	OR	95% CI		OR	95% CI	
Black	2.462	1.505	4.076	2.380	1.468	3.912
Hispanic	0.936	0.392	2.138	1.034	0.455	2.277
Asian/PI	0.305	0.066	1.174	0.352	0.080	1.330
Other	9.650	2.651	34.329	9.826	2.832	33.549
% Black	1.007	0.998	1.017	1.005	0.995	1.015
% Hispanic	0.997	0.985	1.008	0.996	0.984	1.008
% Asian	0.994	0.970	1.016	0.993	0.969	1.017
% Other	1.059	1.005	1.113	1.037	0.984	1.092
Black x % Black	0.990	0.978	1.001	0.991	0.979	1.003
Hispanic x % Black	0.998	0.976	1.020	0.995	0.972	1.017
Asian x % Black	1.022	0.980	1.063	1.012	0.969	1.054
Other x % Black	0.971	0.932	1.007	0.973	0.935	1.008
Black x % Hispanic	1.005	0.987	1.022	1.003	0.986	1.022
Hispanic x % Hispanic	1.009	0.994	1.026	1.007	0.991	1.024
Asian x % Hispanic	1.030	0.997	1.064	1.026	0.994	1.061
Other x % Hispanic	1.003	0.960	1.044	1.003	0.962	1.044
Black x % Asian	1.014	0.975	1.055	1.018	0.978	1.059
Hispanic x % Asian	0.992	0.957	1.027	0.991	0.956	1.026
Asian x % Asian	0.998	0.960	1.037	1.000	0.965	1.037
Other x % Asian	0.972	0.880	1.058	0.980	0.897	1.061
Black x % Other	0.951	0.858	1.052	0.976	0.874	1.082
Hispanic x % Other	0.937	0.844	1.022	0.956	0.865	1.045
Asian x % Other	1.027	0.946	1.120	1.061	0.973	1.157
Other x % Other	0.893	0.801	0.980	0.914	0.822	0.999
Controls						
Age				0.995	0.975	1.015
Age^2				1.001	0.998	1.004
HS Diploma				0.736	0.516	1.075
Bachelors+				0.640	0.424	0.969
US Born				0.908	0.550	1.493
Twins				40.488	27.827	59.264
Triplets+				53.839	2.026	2241.723
Median HH Income (logged)				0.878	0.664	1.165
Intercept	0.029	0.022	0.038	0.065	0.019	0.218
LOOIC	5288.5			4934.9		

Notes: n=9,652 births, OR=odds ratio, 95% CI=95% credible interval, LOOIC=leave-one-out cross-validation information criterion. Reference categories are white for race/ethnicity, less than high school for educational attainment, foreign born for nativity, and singleton for multiple gestation.

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