

ROUTES TO LOW BIRTH WEIGHT (OR NOT): LOCAL, CULTURAL RACISM IN  
EXCEPTIONAL COMMUNITIES

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**Abstract**

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The gap in low birth weight (LBW; weight of less than 2500 grams or approximately 5.5 pounds) between infants born to non-Hispanic black mothers<sup>1</sup> and non-Hispanic white<sup>2</sup> mothers in the US has remained the largest gap in LBW between racial and ethnic groups despite advances in both civil rights and public health practice. While this gap is robust, race itself has no direct, biological effect on patterns of disease prevalence or incidence. Instead, health scholars point to racism as a primary, upstream determinant of persistent gaps in morbidity and mortality, including the gap in LBW, between black and white Americans. While the majority of

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<sup>1</sup> Throughout this dissertation, I will use the term “mother” to describe the parents who gave birth to their children. I acknowledge that at the population level, this may include persons who do not identify as female, woman, mother, or other identities traditionally associated with the act of childbirth. However, natality data for which the statistics presented here are drawn and that I use in my analysis do not allow for identification of the birthing parent outside of the classification of “mother”. As such, I use this term here.

<sup>2</sup> For simplicity, non-Hispanic black mothers will be referenced as “black” and non-Hispanic white mothers will be referenced as “white”.

research on racism and health has relied on self-reported measures of both discrimination and racial attitudes to operationalize racism, these metrics are subject to several biases and often fail to fully account for the variation in health outcomes across racial and ethnic groups. So considered, scholars have recently argued that manifestations of cultural racism may provide insights into the conditions that produce and maintain racial and ethnic health disparities. The research questions proposed here are designed to assess the utility of various area-based measures of racism, some cultural and some structural, in understanding racial disparities in LBW across metropolitan statistical areas (MSAs) in the US. First, I investigate the association between area-based measures of structural racism, informed by fundamental cause theory, and LBW. I find that MSA-level measures of power and prestige have a positive association with the black LBW rate and the black-white LBW ratio. In addition, I find that one measure of unfreedom, racial clustering, may actually operate as a buffer and partially mitigate the negative health consequences of living in an MSA with restricted access to beneficial social connections due to patterns of residential isolation. Second, I use predictive models from the first empirical chapter to identify MSAs with significantly higher or lower observations of the outcomes than expected given model covariates. From the full analytic sample of 301 MSAs, I find that 19 MSAs stand out as “exceptional” in regards to the outcomes. However, these MSAs do not appear to be places that are unequivocally unjust or not in regards to racial differences in measures of structural racism. Lastly, I use historical, geocoded data from Twitter to investigate the racialized social climate of each exceptional MSA as a means to better understand the under- and over-achievement of these communities. I find that, in general, exceptional MSAs have roughly equivalent amounts of positive, negative, and neutral racialized language among Twitter users regardless of whether they have higher or lower rates of the outcome. Thematic analysis

reveals that many tweets included in the analyses are not relevant to the goals of the story.

However, among the tweets that are relevant, most tweets about black people are negative and many are racist. In addition, racialized language on Twitter appears to be gendered in distinct ways as well. Overall, this dissertation shows that combining conventional measures of structural racism with novel measures of cultural racism can provide a more nuanced overview of the social conditions that lead to greater disparities in LBW, as well as those that may protect against these health inequalities.

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In addition, while it may be unconventional, I believe that women tend to downplay ourselves and our efforts and make ourselves small to accommodate others. I would like to break from that path and acknowledge myself and my hard work. I grew up in a small, semi-rural town

in the middle of North Carolina. I went to a school in which the majority of students received free or reduced lunch. My mother was a single mother for much of my childhood, and my maternal grandparents helped raise me. My mother went to college the year before I did, making her the *first woman* and *second person* in our family to attend a four-year university. For this and other reasons, graduate school has been very challenging. I'm proud of myself for what I've done, and I look forward to what I will do. I hope that in the future, my colleagues have backgrounds that are more like mine and if anyone reads this, I hope you take time to acknowledge your hard work as well.

## Chapter 1. Introduction

*“Enough is enough. Race is a social construct and the overwhelming statistics we present are attributable to a broken racist system, not a broken group of women. Evidence-based outrage is the objective, logical conclusion.” - Kacey Y. Eichelberger, Kemi Doll, Geraldine E. Ekpo, and Matthew L. Zerden (2016)*

### 1.1 An Inequality at the Starting Gate

Low birth weight (LBW; weight of less than 2500 grams or approximately 5.5 pounds) is a metric commonly used to signal the health of populations. This is because newborns have not had the opportunity to engage in risk behaviors such as smoking first hand, alcohol use and abuse, or eating high-fat foods. As such, while LBW is certainly a marker of infant health, it is much more so an indicator of the health of mothers. In the United States, the gap in LBW between infants born to black mothers and white mothers has remained the largest gap in LBW between racial and ethnic groups despite advances in both civil rights and public health practice. In 2016, the most recent year for which data are available, 13.68 percent of all live births among black mothers were reported as LBW. Among babies born to white mothers, 6.97 percent of births were reported as LBW (Martin et al. 2018; see Figure 1.1).

Infants who are born LBW are at an elevated risk for numerous health outcomes that manifest over the life course including infant mortality (i.e., deaths within the first year of life), limited cognitive ability, behavioral problems in early childhood, and the development of cardiovascular disease in adulthood among other ailments (Valero et al. 2004). There is also evidence to suggest that LBW becomes an “inherited” trait as infants who are born LBW are more likely to give birth to LBW infants themselves (Alberman et al. 1992). As such, the gap in LBW between babies born to black and white mothers is an “inequality at the starting gate” and a primary public health concern. In addition, the black-white gap in LBW implies that our health system is failing not only black infants, but their mothers as well.

## 1.2 Racism and Health, not Race and Health

LBW is not the only outcome for which we observe a robust association between race and health. For centuries, health researchers and sociologists have documented stark disparities in morbidity and mortality between black and white Americans (DuBois 1906, Krieger 2001). While early investigations into black-white disparities argued that innate differences in biology and disposition were the primary determinants of these health inequalities, the evidence produced over the past few decades is resounding: it is racism, not race, which is a primary cause of black-white disparities in morbidity and mortality (Williams 2012). That is, race in and of itself does not have a direct effect on disease occurrence and biological susceptibilities. Rather, race is a socio political construct used not only to classify human variation based on arbitrary physical characteristics, but also to justify the exploitation of groups defined as inferior and has historically exposed groups racialized as non-white to health risks while simultaneously limiting their access to health-promoting resources (Omi and Winant 2014). Racism is defined here as the totality of beliefs, attitudes, institutional arrangements, and acts that in their consequence, not necessarily their intent, denigrate individuals or groups based on phenotypic characteristics and/or ethnic group affiliation and maintain the racial status hierarchy that privileges individuals and groups racialized as white (Jones 2000, Wellman 1993, Bonilla-Silva 2017).

## 1.3 Racism and Low Birth Weight

Racism is theorized to operate and affect health at multiple levels of social organization through multiple mechanisms. For the case of LBW, three overarching pathways link exposures to racism with the outcome. First, racism produces socioeconomic inequalities that limit access to resources that may reduce the likelihood of LBW. Second, racism produces patterns of residential segregation that isolate black Americans in low-income communities and increase

their exposure to health risks. Third, racism disproportionately exposes black Americans to psychosocial stressors both as a result of inequalities in socioeconomic status and residential mobility as well as the added burden of interpersonal forms of racial discrimination.

### 1.3.1 Social Class and LBW

In the U.S., individuals and the populations they make up are stratified by social class, or one's relative position to others based on economic and social characteristics. While social class is manifest in various forms of capital (social, cultural, symbolic), this concept is most often operationalized based on economic characteristics and measures of human capital.

Socioeconomic status (SES) is the conventional operationalization of social class and typically is based on three metrics: educational attainment, income, and occupational prestige.

African Americans are more likely to occupy lower levels of SES than their white peers. This differential social position is a direct product of historical and contemporary forms of racism in the U.S. As Camara Jones (2000) notes, "...it is because of institutionalized racism that there is an association between socioeconomic status and race in this country". Black Americans have experienced a historical and persistent form of racial prejudice and oppression that includes, but is certainly not limited to, slavery, legal segregation across numerous socioeconomic and geographic spaces, and the overrepresentation of black Americans in the criminal-legal system. In 2016, the median household income for a white household was \$59,083 but was \$36,651 for a black household. In that same year, 8.5% of white households lived in poverty while 22.3% of black households lived in poverty (US Census Bureau). The same, or in some cases larger, disparities exist in Supplemental Nutrition Assistance Program (SNAP; formerly known as food stamps) receipt, wealth, and other measures of economic capital.

Social class is theorized to influence health through two primary pathways. First, high-SES individuals are able to utilize their capital to access resources such as affordable and healthy food, adequate health care, and stable employment. Second, high-SES individuals, by way of their dominant social position, are more likely to feel a sense of control over their lives and less likely to experience the psychosocial consequences of occupying a position of relative disadvantage. Through these mechanisms, individuals who occupy higher levels of SES tend to have better health, across a variety of outcomes (Adler et al. 2007). This pattern holds true across countries (Bloom and Canning 2000), across counties (Dwyer-Lindgren et al. 2017), across communities (Diez-Roux and Mair 2010), within organizations (Marmot 2004), and over time (Link and Phelan 1995).

A prime example of this advantage can be seen in differences in life expectancy by SES. Between 1990 and 2000, groups with 13 or more years of education experienced a 1.6-year increase in life expectancy while the life expectancy of their peers with a high school degree or less remained unchanged (Maera, Richards, and Cutler 2008). Using a more comprehensive measure of 11 indicators of SES, Singh and Siahpush (2006) found the gap between economically advantaged and economically disadvantaged populations grew between 1980 and 2000 from 2.8 to 4.5 years difference in life expectancy at birth. The association between SES and health holds for LBW as well. As mother's education, income, and other aspects of SES increase, the risk for prematurity and LBW decreases. This is partially due to the relationship between SES and other known risk factors for LBW: maternal malnutrition, smoking, alcohol consumption, drug abuse, stress, and access to health care<sup>1</sup>. For example, higher SES may allow mothers to avoid stressful work experiences during pregnancy or to afford the necessary prenatal care to avoid risks for preterm delivery and other complications<sup>1</sup>.

Given the aforementioned association between race and SES, African Americans are more likely to experience health disadvantages inherent to lower socioeconomic standing because they are more likely to occupy these positions. This is partially due to the fact, as Williams (2012; p.283) notes, "... SES is not thus just a confounder of the relationship between race and health but part of the causal pathway that links race to health". The operative word here is "part", as most studies find that racial differences in SES do not fully account for the relationship between race and health. For example, Geruso (2012) found that 80% and 70% of the black-white gap in life expectancy at age 1 for men and women, respectively, can be accounted for by black-white differences in SES and other demographic characteristics (e.g. marital status). Additionally, Braveman and colleagues (2010) find that socioeconomic gradients in health among black Americans were at least as large, if not larger, than differences across blacks and whites. Findings such as this suggest that while differences in SES and other demographic or social characteristics can explain a large amount of the variability in black-white health disparities, they by no means account for all of it. For LBW, researchers have long noted that the health advantages associated with occupying higher levels of SES do not seem to protect black mothers. In fact, black mothers with college and professional degrees are more likely to give birth to LBW infants than white mothers who haven't completed high school (Parker, Schoendord, and Kiely 1994; Lu et al. 2010).

### 1.3.2 Residential Segregation and LBW

Racial residential segregation is a common feature of metropolitan areas in the U.S. and is the product of overt and covert forms of housing discrimination in the form of red-lining, predatory subprime mortgage lending, and restrictive housing covenants. In 2010, 145 MSAs had a dissimilarity index greater than 0.60, meaning that 60% of the black population in these

MSAs would need to move to achieve integration (US Census Bureau). Even when segregation is measured in different ways, not just using the dissimilarity index, African Americans are less likely to live in a census tract with whites (exposure), more likely to live in a census tract with other African Americans (isolation), more likely to live in census tracts that border similarly segregated tracts (clustering), more likely to be located near the center of an urban area (centralization), and more likely to be concentrated in geographically small areas (concentration). When African Americans live in communities with all of these characteristics, they are considered to be hypersegregated (Massey and Denton 1989).

While these patterns are striking, it is critical to note that there is nothing inherently detrimental about living near members of one's own race. Rather, it is the combination of racial inequalities in SES and racial residential segregation that disproportionately concentrates racial minorities in low-income communities (Massey and Denton 1993). This interaction of poverty and racial concentration has profound effects on the opportunities for social mobility afforded to its residents. First, poverty concentration "hollows out" communities as wealthier residents seek housing in higher-income communities and businesses follow suit, restricting the employment opportunities available to residents without the capital, resources, or desires to leave the community (Wilson 2012, Sharkey 2013). Second, residential segregation affects educational opportunities as public schools are funded through local taxes. Additionally, political leaders are more likely to cut spending and social services in predominantly African American communities (Wallace 1991). Therefore, public schools operating in low-income, predominantly African American communities are likely to receive less funding and provide a lower quality of education than schools that operate in predominantly white communities (Orfield and Eaton 1996).

Not only is residential segregation partially caused by racial differences in SES, it perpetuates these differences as well. Even when African American families reach a degree of residential attainment (i.e., the ability to leverage SES and other resources to “buy-in” to a community) that settles them in a middle-class community, they are still likely to be isolated and clustered near lower income communities (Pattillo 2013). Additionally, the social and physical characteristics of predominantly minority communities limit the degree to which residents can engage in prevention behaviors and their degree of exposure to health risks. Predominantly African American communities are less likely to have access to health-promoting resources in the natural and built environment such as quality housing (Bullard 1994), grocery stores (Walker, Keane, and Burke 2010), and green spaces (Pincetl 2003). These same communities are also more likely to be exposed to health risks including environmental toxins and pollutants (Jones et al. 2014), crime (Ross and Mirowsky 2001), and liquor stores (LaVeist and Wallace 2000).

Research on the association between residential segregation and LBW, while extensive, has produced several inconsistencies and counterintuitive findings. Across 225 MSAs, Bell and colleagues (2006) find that higher racial isolation was associated with lower birth weight, higher rates of prematurity, and higher rates of fetal growth restrictions. Similarly, for MSAs within Michigan, Debbink and Bader (2011) find that after adjusting for maternal risk factors and other area-based measures, living in a predominantly African American segregated community was associated with increased odds of LBW. Research by Grady (2006) shows that this pattern holds true in the New York City boroughs, adding that the effects of neighborhood segregation cannot be accounted for by neighborhood poverty alone. However, research on residential racial and

poverty isolation in 228 MSAs by Walton (2009) suggests that segregation increases the odds of LBW among African Americans, but only when coupled with high poverty rates.

While racial and poverty isolation are more commonly used to study the effects of residential segregation on LBW and other birth outcomes, several studies do incorporate measures of clustering or similar constructs such as centralization or concentration into their models. Analyzing data for 3 million births across 261 MSAs, Ellen and colleagues (2000) find evidence that the concentration of blacks in central-city environments and environments with older housing may be more consequential for LBW than measures of racial separation such as the commonly used index of dissimilarity. However, Walton (2009) finds clustering has a similar effect on the likelihood of LBW as isolation does and that the effects of clustering are most pronounced in low-income communities. Contradicting these findings, Bell and colleagues (2006) find that while racial isolation increases the likelihood of LBW, clustering may operate as a partial buffer for these negative effects. They argue that increases in residential clustering among African Americans decreases the likelihood of LBW because these communities may provide social support and cohesion, although they do not test this directly. It is also plausible that residents in racially clustered communities are less likely to be exposed to interpersonal forms of racism than their peers in integrated communities.

Lastly, several studies suggest that the mechanisms that mediate the relationship between residential segregation and infant health operate differently for black and white women. A retrospective study on LBW in Chicago found that not only were black women less likely to live in middle-income neighborhoods than their white peers, the black-white gap in LBW was greater between women in middle-income communities than those in low-income communities. In other words, while living in a low-income community increased the risk of LBW for both black and

white women, black women in middle-income communities did not experience the same minimization of risk as white women in middle-income communities (Collins and David 1990). A separate analysis found that for African American mothers but not white mothers, mean birth weight decreased as the level of economic disadvantage increased. Additionally, for white mothers but not black mothers, increases in perceived levels of social support were associated with increases in infant birth weight. Also, neighborhood level predictors only slightly reduced the unexplained variation in birth weight between black and white mothers (Buka et al. 2003). As this review suggests, the association between residential segregation and LBW is not fully understood.

### 1.3.3 Stress and LBW

The stress paradigm in health research argues that stressful conditions trigger natural, biological responses. While our bodies are evolutionarily well equipped to handle acute stressors (i.e., the “fight or flight” response), chronic over activation of the body’s stress response system has detrimental effects on both physical and mental health outcomes. When we experience a stressor, whether it be getting into a car accident or regular concerns over finances, our hypothalamus-pituitary-adrenal (HPA) axis is activated and our body leaves homeostasis, shifting energy and effort away from long-term biological processes such as bone maintenance and organ function to the stressor at hand (McEwen 1998). To return our bodies to homeostasis, our adrenal cortex produces the stress hormone cortisol in a process known as “allostasis”. When our bodies remain in allostasis longer because over-exposure to chronic stressors has dulled our stress response and requires more cortisol to return our bodies to homeostasis, we experience allostatic load. Allostatic load, measured by several cumulative biological processes (e.g.,

systolic and diastolic blood pressure, glucose, hip-to-waist ratio) is associated with increases in coronary heart disease, inflammatory disorders, and cognitive impairment (Massey 2004).

Racism operates as a source of psychosocial stress through both direct and indirect pathways. Racism indirectly affects health by creating social conditions that disproportionately expose racial minorities to stressors that are based not on racial group affiliation but on other intersecting social categorizations, namely socioeconomic status (SES). These stressors can be collectively considered “products of racism”. For example, individuals with lower levels of SES are exposed to more stressors than their peers in advantaged socioeconomic positions (Thoits 2010). Racism directly affects health by creating social conditions that disproportionately expose racial minorities to stressors that are based on racial group affiliation, including directed racial slurs and other forms of overt racial bias. Even at higher levels of SES, African Americans may experience stressors in the form of explicit anti-black biases (Feagin 1991). Additionally, African Americans who receive constant messages that they are inferior in U.S. society because of their racial identity may internalize these views, further affecting their health and well-being (Williams 1999, Chae et al. 2010, Chae et al. 2014). As such, black Americans are exposed to, or have the opportunity to be exposed to, additional stressors based on their racial identity that their white peers are not exposed to.

Stress is an established risk factor for LBW and has been the focus of many studies seeking to explain the black-white gap in infant health outcomes or other racial and ethnic disparities in infant health. Continuous exposure to stress, whether in the workplace or in private settings, may increase the risk of preterm birth and as a result, the risk of LBW as well (Hedegaard et al. 1996). It is theorized that exposure to stress during pregnancy increase production of the neuropeptide corticotropin-releasing hormone (CRH) which is not only likely

to play a role in activating labor, but if activated early on and throughout the pregnancy may increase the risk of both preterm birth and restricted fetal growth in utero (Wadhwa et al 2004). However, even prior to pregnancy, the effects of chronic exposure to stress begin to take their toll and increase the probability of poor infant health outcomes.

The effects of lifetime, chronic stressors on infant health was popularized in Geronimus' (1992) weathering hypothesis. The thesis posits that black women in the U.S. experience higher rates of exposure to psychosocial stressors (e.g., financial instability, racial discrimination, family members incarcerated) than their peers of other racial and ethnic groups. As a result, black women experience early health deterioration such that their biological age supersedes their chronological age. When black women become pregnant at the average childbearing age (i.e., 25-29 years of age), they have experienced more biological "weathering" than women in other racial and ethnic groups, increasing the likelihood that they will give birth to infants at low birth weights. This thesis is supported by the differential effects of age as a risk factor for low birth weight across racial and ethnic groups. For all women, giving birth between the ages of 15 and 19 or the ages of 35 and 40 increases the likelihood of having an infant that is low birthweight. However, whereas the risk for low birth weight decreases with maternal age up to 35 years for white women, the risk increases steadily across five-year age intervals for black women. Specifically, babies born to white women aged 25-29 years are half as likely to be born LBW than babies born to black women of the same age (Geronimus 1992). Contemporary research also supports the causal relationship between lifetime exposures to stress and LBW or other infant health outcomes arguing that stress responses negatively affect reproductive systems through the same neuroendocrine, behavioral, immune, and vascular mechanisms that affect other physiological systems (Rich-Edwards and Grizzard 2005). Indeed, Geronimus and

colleagues (2006) show that black women in the U.S. have higher allostatic load scores than white women.

Focusing specifically on exposures to racial discrimination as a source of psychosocial stress, we see a similar pattern. Collins and colleagues (2000; 2004) find that exposures to racial discrimination during pregnancy and over the life course are associated with an increased risk for very low birth weight (VLBW; weight of less than 1500 grams or approximately 3.3 pounds), but only exposures over the life course were statistically significant. Similarly, Dominguez et al. (2008) show that lifetime and childhood indicators of perceived racism predicted birth weight and that the results were significant for babies born to African American mothers. Mustillo et al. (2014) also find that black women who report higher levels of racial discrimination were at an elevated risk for LBW compared to white women. Other research suggests that there is an additional effect of reactions to racism on LBW. Carty et al. (2011) show that emotional responses to racism-related experiences are marginally associated with LBW among African American mothers in Genesee and Saginaw counties in Michigan. Lastly, while the outcome of interest was pre-term birth (PTB), not necessarily LBW, Rosenberg and colleagues (2002) find that discrimination experienced at work was a consistent and significant predictor of PTB. Still, Murrell (1996) finds no association between self-reported racism and birth weight, but they do find a positive association between reports of racism and reports of perceived stress.

#### 1.3.4 Gaps & Challenges in the Association between Racism and LBW

While the review above presents compelling evidence that structural manifestations of racism (i.e., racial differences in social class and residential segregation) and interpersonal forms of racism have deleterious effects on the health of black mothers and infants, gaps in this body of research remain. Two of these gaps will be explicitly addressed in this dissertation. First,

research on racism and health in general and racism and LBW in particular has largely relied on the stress paradigm as a theoretical framework. There is good reason for this, as the stress paradigm closes the causal mechanism gap and demonstrates the ways that racism and other social processes “get under the skin” and become embodied (Link 2008; Krieger 2005). With the stress paradigm as an overarching theoretical framework in social epidemiology, researchers interested in the relationship between exposure to racism and health have primarily focused on interpersonal forms of racism (e.g., directed racial slurs, microaggressions) and given relatively less attention to the ways in which racism manifests at the macro-level both structurally and culturally.

As Hicken and colleagues (2018) note, racism in the U.S. is a cultural product, informed by the racialized history of the country and maintained through the dual processes of identification and rationalization. Identification processes include the racialization of individuals based on phenotypic characteristics and the stigmatization of certain groups relative to others based on these racialization processes. Rationalization processes standardize the norms and behaviors of privileged social actors and crystallize these norms as the dominant ideology in a society by which all members of a society are evaluated. The authors (2018) go on to argue that like other manifestations of culture within a society, cultural racism is actualized through structural or institutional forms of racism. At the institutional level, racism manifests in racial residential segregation, access to health promoting information, and racially-coded language in policy among other institutional processes. Racism functions at lower levels of social organization as well and is manifest in both interpersonal interactions (e.g., microaggressions, directed racial slurs) and internalized processes in which members of marginalized racial groups come to accept the negative messages about their own intrinsic value and worth. Put succinctly,

racism is a “social toxin” that permeates all levels of social organization and is theorized to be a fundamental cause of racial and ethnic health disparities in the U.S. (Phelan and Link 2015).

Second, and relatedly, researchers interested in analyzing the associations between macro-level manifestations of racism and health are presented with the challenge of how to measure these constructs. While many researchers have used measures of residential segregation, mass incarceration, and political representation to estimate the association between structural racism and health, conflicting and counterintuitive findings in this body of research suggest that these measures do not fully capture all the ways in which experiences of racism matter for health. The same could also be said for the research on exposures to interpersonal forms of racism and health, which has primarily relied upon self-reported measures of discrimination. While self-report measures avoid the ecological fallacy and eliminate the concern that despite being exposed to racial discrimination at varying levels of social organization, individuals may not attribute their exposures to discrimination as such, these measures also suffer from shortcomings. Notably, these measures are subject to recall as well as social desirability biases. In addition, individuals may not be aware of the racial discrimination they are experiencing, either because this occurs in the “back space” or due to the nature of covert racism. While these implicit forms of discrimination may not result in an interpersonal exposure to stress, they may capture social processes and conditions that are consequential for health. As such, researchers have begun to turn their attention to novel data sources such as Google Trends and Twitter that may be able to circumvent the methodological shortcomings of self-report measures of discrimination. In addition, these data sources may be an appropriate proxy for the racialized social climate of a given area and may capture the covert racial attitudes or cultural manifestations of racism theorized to influence health.

## 1.4 Research Overview

In this dissertation, I answer the question, “What is the association between structural and cultural manifestations of racism and LBW across MSAs in the U.S.?” across three interrelated empirical chapters. First, I investigate the association between area-based measures of structural racism, informed by fundamental cause theory, and LBW. Specifically, I test the association between various MSA-level measures of prestige, power, beneficial social connections, and freedom through a series of regression models. Second, I use predictive models from the first empirical chapter to identify. Lastly, I use historical, geocoded data from Twitter to investigate the racialized social climate of each exceptional MSA to better understand the under- and over-achievement of these communities.

### 1.4.1 Data Sources

Three main sources of data are used across the three empirical chapters in this dissertation. First, data on the outcome, LBW, among babies born to black and white mothers come from natality data files from the National Vital Statistics System (NVSS) of the NCHS for the years 2013 through 2016. These data files are a census of all births that occurred during a given calendar year in the United States, including the District of Columbia and U.S. Territories. The data contain demographic and health data that are extracted from birth certificates, as well as geographic identifiers at the county level, which can be aggregated to the MSA level. Second, data used to create structural manifestations of racism at the MSA level as well as relevant population characteristics come from the American Community Survey 2011-2015 5-year sample available through the U.S. Census. I also supplement these data with a measure of racial inequalities in incarceration which comes from the Incarceration Trends Dataset available through the VERA Institute of Justice. These data sources are used in the first two empirical

chapters. For the third empirical chapter, I use data from Twitter, primarily in the form of historical and geocoded tweets from 2012-2016 available through the Digital OnLine Life and You Project (DOLLY). DOLLY is a repository of billions of geo-located tweets that allows for real-time research and analysis<sup>1</sup>. Twitter data from DOLLY contain latitudinal (y) and longitudinal (x) coordinates in addition to data on screen name, number of followers, hashtags used, and the text of each tweet. This level of geographic specificity allows for data aggregation at any level, including the county and MSA, therefore making DOLLY a worthwhile data set for examining racialized social climates.

#### 1.4.2 Chapter 2

The first empirical chapter (Chapter 2) provides a test of the theory that racism operates as a fundamental cause of health inequalities through four related mechanisms: prestige, power, beneficial social connections, and freedom (or a lack thereof; Phelan and Link 2015). The chapter begins by providing a review of each fundamental cause mechanism and the health research that suggests these mechanisms produce black-white disparities in LBW. I then use data from the ACS to create MSA-level measures of each fundamental cause mechanism. I measure black-white disparities in power and prestige as the black-white gap in occupational attainment, educational attainment, household income, poverty, and unemployment. I measure beneficial social connections as the residential isolation of black households and poor households. I measure “unfreedom” (the absence of freedom) as the gender ratio of black men aged 15-34 to black women of the same age, racial clustering of black households, and the black-white gap in the average daily jail population. Through a series of regression models, I find that power and prestige have a negative association with the black LBW rate and the black-white LBW ratio. I

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<sup>1</sup> For more information on DOLLY, visit <http://www.floatingsheep.org/p/dolly.html>

also find that at least at the MSA-level, disentangling the differences between beneficial social connections and unfreedom are unlikely given current area-level measures of racial inequality available in the ACS. In addition, I find that racial clustering may operate as a partial buffer, although clustering does not negate the health consequences of MSAs with high levels of racial and poverty isolation. This chapter concludes that fundamental cause theory may be a useful framework for investigating the association between aggregate level measures of racial inequality and health.

### 1.4.3 Chapter 3

The second empirical chapter (Chapter 3) builds upon the analysis in Chapter 2 by identifying MSAs that have higher or lower black LBW rates and/or higher or lower black-white LBW ratios than we would expect given the fundamental cause mechanisms and relevant population characteristics used in regression analyses. To identify these MSAs, I calculate the standardized residuals from the fully adjusted models for both outcomes and select the MSAs with standardized residuals 2 standard deviations above or below the mean for each outcome. In total, I identify 19 MSAs: 5 MSAs have lower black LBW rates than expected, 8 have higher black LBW rates than expected, 5 MSAs have lower black-white LBW ratios, and 6 MSAs have higher black-white LBW ratios. I provide a descriptive review of the 19 exceptional MSAs, focusing primarily on the six MSAs that identified as exceptional regarding both outcomes. I find that these MSAs do not appear distinct in the measures of racial inequality included in the models or regarding other characteristics. Several MSAs stand out regarding one or two predictors, but these MSAs by no means appear to be places that are unequivocally unjust or unequivocally equitable. As Caldwell (1986) and Kuhn (2010) note in their analyses of countries with exceptional mortality rates, there is no “one-size-fits-all” route to low birth weight.

#### 1.4.4 Chapter 4

The final empirical chapter (Chapter 4) again builds upon the analyses from the two previous chapters. The analyses in Chapter 4 intend to capture aspects of racialized social climates that may provide insights into the under- and over-achievement of the 19 MSAs identified as exceptional in Chapter 3. To do so, I use two datasets comprised of Twitter data to build and apply a computer algorithm to identify tweets as “about black people” and as “positive”, “negative”, or “neutral”. In addition to computational methods and quantitative analyses of the data, I qualitatively analyze a random subsample of 2280 tweets using a team of 26 undergraduate researchers (UGRs). I find that the computer algorithm used to identify tweets based on subject and sentiment is often in disagreement with the human annotations from UGRs, although there are times that the computer algorithm appears to be “correct” while the human annotations appear to be “incorrect”. Of the tweets that UGRs identified as relevant to the scope of this study, negative tweets about black people were most common, many of which were also categorized by the UGRs as racist. UGR research memos are used to provide rich description of the themes that appeared within the text of each tweet. A contribution of this analysis is the difference in language about black women and men. Negative language about black women tends to be more direct and overt while negative language about black men tends to be more global and relies on generalizations and stereotypes. This is particularly true when black women and men are sexualized as black women’s bodies are often fetishized or labeled as undesirable while black men are framed as sexual aggressors, particularly toward white women. UGR memos also provide useful insights into how coders make decisions, a critical aspect of methodology currently missing from research on the association between textual data sources like Twitter and health. I conclude that previous studies that use word-search queries may be

overestimating the association between racialized language on social media, a proxy for racialized social climates, and health.

### 1.5 Conclusion

The final chapter of this dissertation summarizes the theoretical and methodological relevance of the findings from the previous three empirical chapters. Study limitations, remaining gaps in the literature, and suggestions for future research are also discussed including opportunities to include individual level data on maternal characteristics, MSA-level data on additional characteristics of the natural, built, and social environment as well, and to investigate micro-level processes further. Overall, this dissertation contributes to the growing and substantial evidence that racism is a fundamental cause of health inequalities between black and white Americans.

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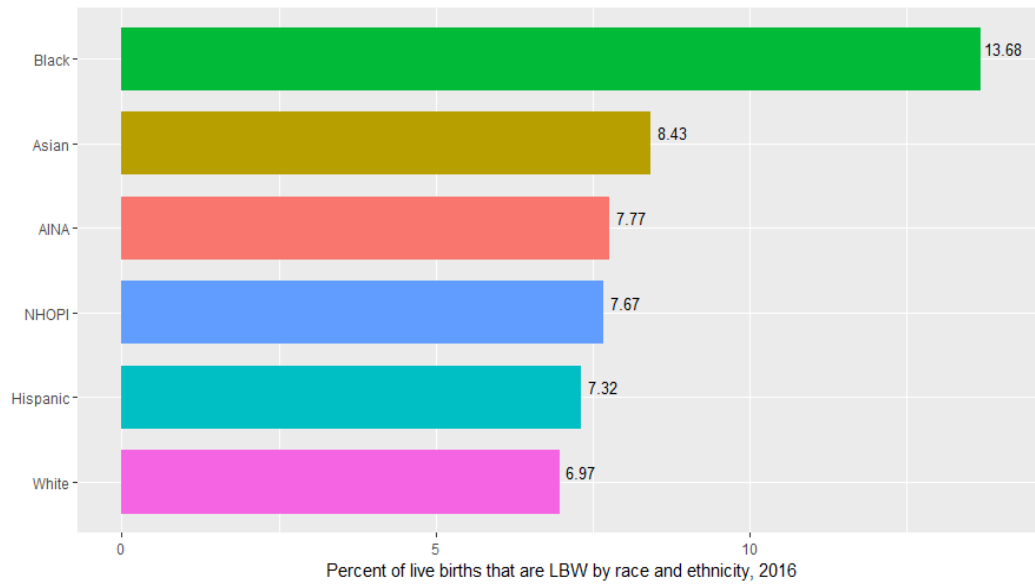


Figure 1.1. Low Birth Weight by Race and Ethnicity, 2016

## Chapter 2: Racism as a Fundamental Cause of Low Birth Weight: A Test of the Theory

### 2.1. Introduction

As noted in Chapter 1, the gap in LBW between infants born to black mothers and white mothers in the US has remained the largest gap in LBW between racial and ethnic groups despite advances in both civil rights and public health practice. While this gap is robust, race itself has no direct, biological effect on patterns of disease prevalence or incidence. Instead, health scholars point to racism as a primary, upstream determinant of persistent gaps in morbidity and mortality, including the gap in LBW, between black and white Americans. Racism is theorized to operate and affect health at multiple levels of social organization as a *fundamental* cause of racial and ethnic health disparities in the US. However, the ways in which structural manifestations of racism such as differences in socioeconomic status, residential segregation, and mass incarceration contribute to racial disparities in LBW are not fully understood.

This study seeks to contribute to the body of knowledge on racism and LBW by testing the theory that racism operates as a “fundamental cause” of the black-white gap in LBW. While fundamental cause theory is often referenced in population health research, the associations between fundamental cause mechanisms and health outcomes have not been evaluated fully. This study expands upon previous research by including metropolitan level measures of occupational prestige, educational attainment, and mass incarceration in addition to traditional measures of poverty and segregation to predict the rate of black LBW as well as the black-white gap in LBW across metropolitan areas. I also assess the validity of various measures of structural racism and the utility of fundamental cause theory for understanding the persistent black-white gap in LBW.

## 2.2 Theoretical Orientation

Phelan and Link (2015) explicitly name racism as a fundamental cause of racial and ethnic health disparities. Fundamental cause theory (FCT) argues that certain social conditions operate as fundamental causes of disease, meaning that they are causes for which the resultant health effects cannot be eliminated by addressing the mechanisms that link the fundamental cause to disease. In other words, if one could precisely measure racism (or any other fundamental cause), then its relationship to health outcomes would not be attenuated when any other control variables were accounted for. This is because fundamental causes influence multiple disease outcomes through multiple replaceable mechanisms. These mechanisms are open to replacement because socially advantaged populations (i.e. high socioeconomic status Whites in the US) have access to a set of flexible resources—meaning these resources can be used in different ways in different situations—which situate them favorably to take protective action against and adapt to changing risk factors. As such, the relationship between the fundamental cause and disease is maintained over time as risk factors and disease etiology change (Link and Phelan 1995).

In naming racism as a fundamental cause of health inequalities, Phelan and Link (2015) note that while differences in socioeconomic status (SES) explain a great deal of the variation in health outcomes across racial and ethnic groups, these socioeconomic differences are unable to fully account for these disparities. Phelan and Link (2015) argue that while the relationship between SES and health is robust (Adler et al 2007), research on the relationship between race, SES, and health suggests that African Americans have not experienced the same health returns to social and/or economic mobility as their white peers (Williams 1999). As such, they identify four race-specific flexible resources that maintain the relationship between racism and health.

*Prestige* is defined as the honor or deference attached to a person or group, *power* as the ability to control others, *beneficial social connections* as social relationships that are economically and socially advantageous (i.e., have high social capital), and *freedom* as the ability to control one's own life circumstances.

Researchers have long noted that the health advantages associated with occupying higher levels of SES do not seem to apply to the case of LBW, as African American mothers with college and professional degrees are more likely to give birth to LBW infants than white mothers who haven't completed high school (Parker, Schoendorf, and Kiely 1994; Lu et al 2010). This trend supports the general thesis of FCT, and implies that addressing the risk factors that are believed to cause LBW (e.g., current socioeconomic status, maternal health behaviors, prenatal care, and psychosocial stress) will not fully account for or remedy this health disparity (Lu and Halfon, 2003). Research on the causes of the black-white gap in LBW and the elevated rates of LBW among black infants suggests that prestige, power, beneficial social connections, and freedom may operate as manifestations of racism that put black mothers at a disproportionate risk for LBW above what their SES would imply.

While Phelan and Link (2015) broadly describe the ways that prestige, power, beneficial social connections, and freedom influence racial and ethnic health disparities, it is worth elaborating on these mechanisms here with a specific focus on LBW. In the following sections, I describe the body of research on each of these mechanisms and the pathways through which they are believed to influence health. For each mechanism, I describe the pathways that manifest in differences in SES as well as the pathways that produce differential effects on health that cannot be fully explained by differences in SES. When possible, I will highlight key findings on the association between each race-specific flexible resource and LBW. If no research is available on

LBW specifically, I will instead review research on related, although certainly not identical, birth outcomes including very low birth weight, preterm birth (PTB), infant mortality, and small for gestational age (SGA)<sup>2</sup>.

### 2.2.1 Prestige

Prestige is conceptualized as the “social honor” attached to individuals or social groups (Weber 1946). In sociological research, prestige is commonly operationalized as the prestige held within a certain occupation. Occupational prestige is commonly measured using a “reputational approach” in which respondents to a nationally representative survey are asked to judge the prestige of various occupations (North and Hatt 1947). The National Opinion Research Center (NORC) occupational prestige scale lists physicians, lawyers, and computer scientists as some of the most prestigious occupations and domestic workers, short-order cooks, and parking lot attendants as some of the least prestigious occupations (Davis et al n.d.). In other words, within US society, people who work as short-order cooks are considered less honorable or of a lower status than people who work as lawyers.

Occupations are not the only social categories for which people hold implicit evaluations of prestige. Of specific interest to this study are the differential evaluations of prestige, or honor, on the basis of race. Results from the 2018 General Social Survey (GSS) suggest that 24% of respondents held beliefs that black people are lazy, compared to 13% for white people. There were similar disparities in beliefs about intelligence among GSS respondents, although they were less pronounced (10% and 8% unintelligent, respectively; GSS Data Explorer 2019). Similarly, analyses by van Ryn and Burke (2000) found that physicians are more likely to believe that black

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<sup>2</sup> Very low birthweight refers to births of less than 1500 grams or approximately 3.3 pounds, preterm refers to births that occur before 37 weeks gestation, infant mortality refers to deaths within the first year of life, and small for gestational age refers to births below the 10th percentile for weight for gestational age.

patients will abuse alcohol and drugs and that black patients have low levels of education compared to white patients. As a final illustration, Pager (2003) found that black low-wage job applicants *without* a criminal record were less likely to receive a call back than their white peers *with* a criminal record. Pager (2003) argues that this is due to a belief that black applicants, by nature of their race, were prone to criminal behavior regardless of having a criminal record or not.

Differential evaluations of prestige based on race may affect health through two primary pathways. First, differential evaluations of prestige lead to differential access to resources that can be mobilized in various ways such as moving into neighborhoods with more health resources and fewer health risks, accessing health insurance through an employer or privately, and purchasing products or services intended to maintain or improve health status. As noted above, differential evaluations of honor (e.g., propensity to criminal behavior or drug abuse, intelligence, work ethic) on the basis of race may restrict access among racial minorities to occupations that are seen as more prestigious and commonly pay higher wages and offer more robust benefits. Analyses by Grodsky and Pager (2001) suggest that even when educational attainment and other human capital variables are accounted for, black workers are concentrated in occupations with lower levels of prestige and lower average earnings than their white counterparts. To be clear, the devaluation of one's prestige based on race is a form of interpersonal racial discrimination, primarily by hiring managers. As such, the devaluation of prestige based on race produces a reciprocal relationship with occupational prestige: if black workers are unable to secure prestigious occupations relative to white workers, despite their qualifications, then their under-placement in the occupational prestige hierarchy may lead to further devaluations of prestige or at the very least, confirm these devaluations.

Second, differential evaluations of prestige based on race affect health through differential exposures to psychosocial stressors. These exposures may occur across social settings. In the workplace, Forman (2006) finds that black men in middle-class occupations who perceived higher levels of racial segmentation in their workplaces (i.e., black workers are present in the space but they are relegated to menial, low-level tasks) were more likely to report depressive symptoms, lower levels of self-efficacy, and lower levels of life satisfaction than their black male peers in lower-wage occupations. This suggests that evaluations of honor and other capabilities do not stop at the hiring process and that black workers who are able to secure middle-class, well-paying occupations may be “succeeding more and enjoying it less” (Hochschild 1995). This is supported by Grodsky and Pager (2001), who find that within occupations, racial gaps in earnings are greater among high prestige occupations than among low prestige occupations. For example, black physicians earn 80 cents to every dollar that white physicians earn, while black kindergarten teachers actually earn slightly more than white kindergarten teachers, although the difference is only by a few cents. Findings like these suggest that as African American workers attain higher levels of social status, they are not rewarded equally to their non-black peers and experience psychological distress in the face of these inequalities.

Outside of work, black Americans are also likely to experience status degradation in other social interactions. As Feagin (1991) notes in his study of anti-black discrimination among middle-class African Americans in public spaces, “No matter how affluent and influential, a black person cannot escape the stigma of being black, even when relaxing or shopping”. Recently, Grundy (2017) both analyzes and provides a personal account of racial discrimination experienced by black academics. In her essay on the nature of racialized attacks against black

academics, she explicitly notes that these attacks are “driven by anti-blackness, not anti-intellectualism”. Indeed, using various measures and methods, researchers have consistently shown that white Americans hold anti-black biases, even when SES is controlled for (Nosek et al 2007; van Ryn and Burke 2000). These prejudicial beliefs, when enacted and directed towards individuals, are a form of chronic stress that affects the physical and mental health of black Americans.

### 2.2.2 Power

Power is defined as the “chances of a [person]...to realize their own will in a communal action” (Weber 1946). Put differently, if a member of a group is able to decide the course of action that group takes, they have power. As was the case with prestige, power is often operationalized as a characteristic of occupations. Additionally, access to power is likely dependent on evaluations of prestige, although the two concepts are not equivalent. Consider, for example, an assistant professor in an academic department at a given university. This person certainly has a substantial amount of prestige or social honor attached to them (the NORC occupational prestige scale supports this) but their low rank within their occupational hierarchy likely confers limited power in faculty meetings and other departmental or university affairs.

In stratification research, power is commonly measured at the occupational level based on a worker’s capacity as a supervisor or manager, their ability to hire and fire others, and the degree to which they influence pay rates (Elliot and Smith 2004). Research on promotion decisions suggests that, even when job tenure, skills, and education are accounted for, black workers are less likely to receive a promotion than their white counterparts. Mixed-methods research using verified workplace discrimination cases shows African American workers are at a greater risk for discriminatory firing and are less likely to be promoted or hired even when they

possess the technical skills necessary for the position and in some cases, are more qualified than their white applicant peers (Mong and Roscigno 2009; Ortiz and Rosigno 2009). Additional analyses using the Panel Study of Income Dynamics (PSID) show that black workers, regardless of gender, wait longer for promotions than their white male counterparts and that the effects of race on promotion to managerial positions is most pronounced in the private sector (Wilson 1997, Maume 1999). Elliot and Smith (2004) find a primary mechanism in the acquisition of workplace power is homosocial reproduction: hiring committees are more likely to hire people that are similar to them, including similarities based on race and gender. In other words, the lack of black workers in positions of power within organizations has the potential to reproduce these inequalities. In this way, racial differences in power are informed by differential evaluations of honor (i.e., racial discrimination) and therefore, influence health through similar pathways as prestige (e.g., access to socioeconomic resources and exposures to psychosocial stressors). If black workers are limited in their ability to secure promotions, particularly to supervisory positions, within their own workplace then they will be limited in their access to economic resources and exposed to more psychosocial stressors.

While much of health research has focused on control over one's own life (e.g., autonomy, freedom, mastery; reviewed in subsequent sections), relatively little health research has been dedicated to understanding how the successful control of others influences health. While not identical to the concept of power described here, two studies examining distributions of equivalent concepts and their effects on LBW are worth noting. First, Meyer et al. (2010) find that as workplace substantive complexity increased, the risk of LBW decreased for black working mothers. The concept of substantive complexity was measured using various characteristics of work, such as deductive reasoning and making decisions, that likely capture

aspects of power in the workplace. Meyer et al. (2010) go on to note that black women, despite their credentials, are less likely to occupy jobs with a high degree of substantive complexity relative to their white and Hispanic peers and that this mismatch between skills and the experience of work is a source of stress for working mothers. Second, LaVeist (1992, 1993) shows that within segregated communities, black political power can counteract the negative effects of poverty concentration on birth outcomes. LaVeist (1992) notes that what might seem like the most obvious explanation of this association, that black elected officials would allocate resources in a way that improves the health of residents, is spurious. Rather, this association is produced by community organizing which increases black political representation and improves the material conditions of black residents' lives. In other words, while power is certainly playing a role in this association, it is the power of communities and not necessarily that of elected officials that is improving health.

### 2.2.3 Beneficial Social Connections

As just noted, neighborhoods play a powerful role in the health and well-being of residents. While much research has been dedicated to the physical aspects of communities (e.g., quality housing, grocery stores, and green spaces) the social aspects of communities are equally important. Indeed, access to social networks is heavily structured by residential location and the individuals and resources within neighborhoods. Unfortunately, access to certain social groups and social resources is not evenly distributed across communities in the US, where racial residential segregation is common (see Chapter 1). It is theorized that the lack of economic and educational opportunities afforded to low-income, predominantly minority communities limits access to beneficial social connections among residents, in turn contributing to health inequalities across communities (Diez Roux and Mair 2010; Williams and Collins 2001).

In regard to health, there are two primary pathways through which social connections are believed to affect health. First, access to beneficial social connections may increase the likelihood of securing a well-paying, prestigious job. That is, even once human capital variables such as education and previous work experience are accounted for, having a social connection that can be leveraged to gain knowledge about or secure access to a better job would produce a health benefit in the form of better wages, increases in prestige and power, and improved self-esteem, among other factors. In this way, beneficial social connections would be likely to improve health through improvements in economic and social standing. In *The Truly Disadvantaged* Wilson (2012) argues that residents in low-income, racially segregated communities have limited access to social relationships that are economically and socially advantageous. Wilson (2012) goes on to argue that this form of social isolation limits the ability of residents to secure well-paying jobs through referrals, access to mentors for black youth, and other mechanisms related to the strength and spread of one's social network.

Stratification research suggests that community members do call on their neighbors in seeking out job referrals and that the availability of these neighborhood-based referrals increase earnings and other labor market outcomes (Bayer et al. 2008). However, some individuals are more reliant on these informal job search processes than others. Elliot (1999) shows that workers with lower levels of education in high poverty neighborhoods primarily rely on informal social networks and neighbors to get jobs, while the same is not necessarily true for their peers with similar levels of education living in low poverty communities. Furthermore, the availability of neighborhood-based job referrals can produce large increases in earnings and other labor market outcomes (Bayer et al. 2008). Additionally, racial minorities may rely on insider referrals from neighbors and other members of their social networks more often than whites as a result of

residential segregation, racial discrimination, and other gatekeeping processes (Elliott 2001; Loury 2006). However, it should not be assumed that the mere presence of a social network will produce economic benefit. While Wilson (2012) argued that black residents of low-income communities had restricted social networks, Smith (2008) finds that the networks of the black urban poor are larger, more diverse, more wide-ranging, and much less detached from the mainstream than originally thought. Rather than limited networks, Smith (2008) argues that it is limited trust between network members that limits access to employment for black residents in low-income communities. That is, neighborhood members with jobs may be less likely to recommend their community members that they perceive to be unreliable, fearing repercussions from their employers.

Second, beneficial social connections have been shown to have a direct effect on health separate from the effects of social connections on SES. A vast body of research suggests that the quantity and quality of social relationships influence the likelihood of engaging in certain health behaviors (both prevention and risk behaviors), improves psychosocial well-being, and buffers the negative physiological consequences of stress accumulation (Umberson and Montez 2010). Here, the relationship between beneficial social connections and health can be positive or negative. For example, individuals with strong social ties may be able to call upon their social networks in time of need. This access to social support has been shown to benefit both physical and mental health. However, social networks may also influence the likelihood of engaging in risk behaviors such as smoking, alcohol misuse and abuse, and disordered eating. Regardless, these examples show that social connections have effects on health above the ability to leverage those social connections for economic gain.

The research on the association between residential segregation in general, and racial isolation in particular, suggests that segregation matters for LBW and other infant health outcomes (Bell 2006; Debbink and Bader 2011), but the mechanisms through which this relationship is produced remain unclear. Several analysts suggest that racial residential segregation is only detrimental to infant health when coupled with neighborhood levels of socioeconomic disadvantage (Walton 2009; Messer et al 2010). However, other analyses suggest that neighborhood SES cannot fully account for racial disparities in birth outcomes across segregated communities or that these effects differ by mother's race (Grady 2006; Collins and David 1990). Additionally, research on racial clustering across neighborhoods suggests that isolated, predominantly black communities may produce strong social networks that buffer, although do not fully attenuate, inequalities in LBW (Bell et al 2006). While there are other studies on the association between segregation and LBW, PTB, and other birth outcomes, this brief review suggests that it is still unclear exactly how residential segregation affects LBW, but that SES isolation may be a primary contributor to the black-white gap in LBW within MSAs.

#### 2.2.4 Freedom

Freedom is defined as the ability to control one's own life circumstances (i.e., mastery, autonomy; Sen 1999). "Unfreedom", then, is a partial or total lack of control over one's life circumstances. Population health researchers interested in individual levels of freedom, or a lack thereof, commonly incorporate measures of "mastery" into their analyses, a concept that is synonymous with the definition of freedom provided above. Few studies have directly measured the effects of mastery on birth outcomes. Research by Goldenberg et al. (1996) shows that while black mothers have higher rates of PTB than white mothers, black mothers also have higher levels of mastery compared to white mothers. In fact, lower levels of mastery were predictive of

intrauterine growth restriction (IUGR; a proximate cause of LBW) among white mothers, but not among black mothers. Likewise, Misra and colleagues (2001) found no effects of mastery on the likelihood of PTB once models were adjusted for known confounders. While further research on the effects of a lack of control over one's destiny on birth outcomes is warranted, health research more broadly suggests that a lack of autonomy is a risk factor for numerous health outcomes (Wallston 1987; Wallerstein 1992).

Still, mastery is not the only operationalization of unfreedom available to health researchers. Turning again to neighborhood effects, clustering may provide a crude measure of the effects of historical and contemporary forms of housing discrimination. Research on segregation among middle-class African Americans suggests that even when African American families reach a degree of residential attainment (i.e., the ability to leverage SES and other resources to "buy-in" to a community) that settles them in a middle-class community, they are still likely to be clustered near other African American communities with varying degrees of socioeconomic deprivation. That is, middle-class African American households have experienced and continue to experience overt and covert forms of housing discrimination in the form of red-lining, predatory subprime mortgage lending, and restrictive housing covenants that impinge on their ability to move into middle-class, predominately white communities which also tend to have more health resources and fewer health risks.

While racial and poverty isolation are more commonly used to study the effects of residential segregation on LBW and other birth outcomes, several studies do incorporate measures of clustering or similar constructs like centralization or concentration into their models. Analyzing data for 3 million births across 261 MSAs, Ellen and colleagues (2000) find evidence that the concentration of blacks in central-city environments and environments with older

housing may be more consequential for LBW than measures of racial separation such as the commonly used index of dissimilarity. However, Walton (2009) finds clustering has a similar effect on the likelihood of LBW as isolation does and that the effects of clustering are most pronounced in low-income communities. Contradicting these findings, Bell and colleagues (2006) find that while racial isolation increases the likelihood of LBW, clustering may operate as a buffer for these negative effects. They argue that increases in residential clustering among African Americans decreases the likelihood of LBW because these communities may provide social support and cohesion, although they do not test this directly. An additional explanatory mechanism is political empowerment and representation in clustered communities. However, of the studies that have measured the effect of political representation on birth outcomes, one study finds that an increase in black political power is protective for post-neonatal mortality while the other finds that there is no effect of this same predictor on PTB (Lavesit 1992; Margeirson, Perez-Patron, and Cubbin 2017). So considered, the effects of racial residential clustering on LBW is inconsistent and warrants further exploration.

Another manifestation of unfreedom theorized to affect birth outcomes such as LBW is mass incarceration. Incarceration is an extreme and severe form of unfreedom and Phelan and Link (2015) note that in regards to health, “An imprisoned person does not have the freedom to avoid violent victimization, to benefit from family and friends’ social support, and, possibly, to exercise and eat healthful foods” (pp. 319). In addition, incarcerated or formerly incarcerated persons are unable to participate in civic life, earn a living wage during or after imprisonment, unable to receive social services, and may become partially or fully isolated from their families and friends (Alexander 2010). Sadly, for young black men in the US with a high school degree, GED, or less, imprisonment is an all too common occurrence. For this subset of the population,

the risk of imprisonment over the life course is over five times greater than for their white peers of the same age with similar levels of educational attainment (Pettit and Western 2004). The effects of mass incarceration spill over from the individuals experiencing imprisonment into their families, friends, and communities.

These spillover effects may significantly influence the health of black women. While early research on the effects of partner imprisonment on black women's health focused on the spread of HIV/AIDS and other sexually transmitted infections (STIs), Lee and Wildeman (2013) argue that imprisonment of partners and family and community members also affects black women's physical health. Focusing on the case of cardiovascular disease (CVD), they argue that mass incarceration produces higher levels of CVD among black women through three mechanisms: diminished SES for the family or household, compromised family function (e.g., the loss of emotional or social support, shared child care labor), and stress proliferation. Given the etiology of LBW, it is not a far leap to apply a similar framework to the effects of incarceration on LBW, particularly through the weathering hypothesis.

There is a sizeable body of research examining the effects of parental incarceration on child health and well-being, focusing primarily on childhood behavior and emotional development. Wildeman (2010) finds that paternal incarceration (e.g., having a father who has been or currently is incarcerated) is associated with increased physical aggression in five-year old boys. Wildeman and Turney (2014) also find that maternal incarceration (e.g., having a mother who has been or is currently incarcerated) is associated with higher levels of behavioral problems, as reported by teachers and caregivers. Also investigating the effects of maternal incarceration on children's well-being, Turney and Wildeman (2015) find that the effects of maternal incarceration are the most severe for children whose mothers are the least likely to

experience incarceration. Conversely, for children whose mothers are the most likely to experience incarceration, the effects on children's health is largely inconsequential. While this finding may seem counterintuitive, it is not dissimilar from other findings in health research that show that major or traumatic life events have the greatest consequence on those who were the least likely to expect or experience them, although the mechanisms that produce this pattern deserve further attention.

Focusing on birth outcomes, researchers have traditionally been interested in the effects of maternal incarceration during pregnancy on birth outcomes. Perhaps surprisingly, early research by Martin and colleagues (1997) found that a higher number of pregnancy days spent incarcerated was associated with higher infant birth weight. In their conclusion, the researchers argue that this improvement in birth weight is likely due to the availability of prenatal care among a group of mothers who would not have received this care otherwise. Howard and colleagues (2008) find that for 360 mothers who gave birth during incarceration, the effects of time during pregnancy at which imprisonment began (e.g., during the first or second trimester) on birth weight and gestational age at birth varied by race, with black mothers experiencing no significant effects of the timing of incarceration. More recently, Wildeman (2012) examined the effects of paternal incarceration on infant mortality, finding that infants of recently incarcerated fathers have twice the risk of mortality than other infants, but only if the father was not abusive. As with other studies on incarceration and child health, the effects of parental imprisonment are concentrated among children whose parents had the lowest risk of becoming incarcerated. For children whose parents were already at a higher risk of incarceration, the effects are often null, implying that incarceration is one of a bundle of disadvantages that put these children at a heightened risk of negative health outcomes.

In addition, Roberts (2004) notes that the effects of mass incarceration on health is not limited to the effects of paternal and/or maternal incarceration on early childhood and infant health. Mass incarceration also affects communities by decreasing economic and social capital, distorting social norms, destroying social citizenship, and increasing surveillance, all of which are established risk factors for morbidity and mortality. Indeed, Hatzenbuehler and colleagues (2015) find that even when individual incarceration histories and traditional risk factors are considered, residents in communities with high prison admission rates were more likely to meet the diagnostic criteria for major depressive disorder and generalized anxiety disorder. Pouget and colleagues (2010) also find evidence suggesting that living in a community that has been disproportionately affected by mass incarceration has significant effects on the number of sexual partners residents have, a known risk factor for STIs. Focusing on birth outcomes at the state-level, Wildeman (2012) finds that as the state imprisonment rate increases, total infant mortality, black infant mortality, and the black-white inequality in the infant mortality all increase. So considered, mass incarceration is a public health issue that affects the physical and mental health of communities. Given the patterns of mass incarceration across racial and ethnic groups in the United States, this burden disproportionately falls on African American communities.

#### 2.2.5 Conceptual Model and Research Questions

The review presented here intends to demonstrate the plausible effects of the four race-specific flexible resources identified by Phelan and Link (2015)—power, prestige, beneficial social connections, and freedom—on the likelihood of LBW among babies born to black mothers. As noted at several points in the review, the mechanisms that may link these four concepts to LBW, such as socioeconomic position and exposure to chronic stressors or traumatic life events, likely overlap. The conceptual model provided below in Figure 2.1 shows how these

four resources interact to produce differences in SES between black and white Americans as well as the differences in these resources that cannot be fully accounted for by differences in SES.

This conceptual model and the review provided above expand on the original articulation of racism as a fundamental cause by Phelan and Link (2015). Importantly, this model assumes that racial differences in prestige, power, beneficial social connections, and unfreedom are influenced by historical and contemporary manifestations of racism. Likewise, this model shows that racial differences in these resources influence both racial differences in SES (e.g., education, wealth, income) as well as racial differences in mechanisms that have a direct effect on health (e.g., exposure to racism, devaluation of self). For example, racial differences in the devaluation of human capital and other skills is a racialized process. These processes determine access to and utilization of health resources as well as exposure to psychosocial stressors, producing disparities in LBW. To test the association between each FCT mechanism and LBW, I use data from the National Center for Health Statistics (NCHS) and the American Community Survey (ACS), and ask the following:

1. Do the four race-specific flexible resources identified by Phelan and Link (2015)—power, prestige, beneficial social connections, and freedom—explain variation in the rate of low birthweight (LBW) among babies born to black mothers?
2. Do the four race-specific flexible resources identified by Phelan and Link (2015)—power, prestige, beneficial social connections, and freedom—explain the relative gap in low birthweight (LBW) between babies born to black mothers and babies born to white mothers?

### 2.3 Data and Methods

Data for the analysis come from three primary sources. First, Natality Data from the National Vital Statistics System (NVSS) of the NCHS for the years 2013 through 2016 are used to create the dependent variables. These data files are a census of all births that occurred during a given calendar year in the United States, including the District of Columbia and US Territories. The data contain demographic and health data that are extracted from birth certificates, as well as geographic identifiers at the county level, which can be aggregated to the MSA level. To create the key independent variables, power, prestige, beneficial social connections, and freedom, I use data from the ACS 2011-2015 5-year sample available through the US Census. I gathered data on necessary demographic and economic characteristics at the MSA level as well as geographic boundary files to create measures of segregation. Lastly, I supplement the measures of freedom in the ACS (described below) with jail population data for 2011-2015 from the Incarceration Trends Dataset, compiled by researchers at the Vera Institute of Justice.

The ACS and Natality data were linked using 2015 US Census delineations for tracts, counties, and MSAs. For this analysis, I restricted the level of data aggregation to the MSA. MSAs are delineated by the US Office of Management and Budget (OMB) and are composed of one or more whole counties or county equivalents, such as parishes or municipios. MSAs also include counties that contain core urban areas with populations of 50,000 or more. In 2015, the US Census collected data for 383 MSAs in the US and Puerto Rico (US Census Bureau 2010). From the universe of MSAs, I applied several exclusion criteria which I describe below, in order to create my dependent and independent variables.

### 2.3.1 Outcome Variables

Data for the outcome variables, the rate of LBW among babies born to black mothers and the black-white LBW ratio, come from the NCHS Natality files. To construct the outcome variables, I requested individual-level birth data for all babies born in the United States and all US territories between January 1, 2013 and December 31, 2016 from the National Association for Public Health Statistics and Information Systems (NAPHSIS). The data set contained information on 15,883,784 unique births.

Based on the goals of this research project and previous research on the etiology of LBW, I restricted my natality data sample in several ways, the effects of which are shown in Table 2.1. First, I removed all births to mothers who are not identified as non-Hispanic white or non-Hispanic black. Second, I removed all non-singleton births given that multiple births (e.g., twins, triplets) may be LBW for reasons that are unrelated to the reasons that singletons are born LBW (Blondel and Kaminski 2002). Third, I remove all births that occur at less than 37 weeks gestation and all births that occur at more than 42 weeks gestation, thereby excluding pre-term and late-term births, respectively. In the NCHS data, the majority of gestational estimates are calculated based on last menstrual period (LMP) and a small percentage are calculated based on obstetric estimates (OE) when LMP estimates were unavailable or inconsistent with other birth information. Records for which both OE and LMP estimates were unavailable were removed from the sample (CDC 2013). Fourth, I removed all observations for which birth weight data were missing as well as any births recorded as less than 500 grams or greater than 6000 grams due to the possibility of misclassification error (Walton 2009). Additionally, infants born at less than 500 grams are considered non-viable and infants born at over 6000 grams are considered very large for gestational age (e.g., extreme macrosomia), an outcome with a distinct etiology.

Fifth, I excluded all births that occurred outside of census-designated MSAs in all 50 US states and the District of Columbia (D.C.) using the 2015 MSA delineation files to create a county-to-MSA crosswalk. Lastly, I pooled data across all years available before excluding all MSAs in which fewer than 100 births to both black and white mothers occurred between 2013 and 2016.

To construct the first outcome variable of interest, the rate of LBW among babies born to black mothers, the total number of LBW births to black mothers was divided by the total number of births to black mothers for each MSA. To construct the second outcome of interest, the ratio of black LBW births to white LBW births, I divided the rate of LBW among babies born to black mothers by the rate of LBW among babies born to white mothers.

$$(1) \text{Black LBW Rate} = \frac{\text{Number of LBW Births to Black Mothers}}{\text{Total Number of Births to Black Mothers}}$$

$$(2) \text{Black} - \text{White LBW Ratio} = \frac{\frac{\text{Number of LBW Births to Black Mothers}}{\text{Total Number of Births to Black Mothers}}}{\frac{\text{Number of LBW Births to White Mothers}}{\text{Total Number of Births to White Mothers}}} = \frac{\text{Black LBW Rate}}{\text{White LBW Rate}}$$

### 2.3.2 Independent Variables

The key independent variables for this analysis are based on the four race-specific flexible resources identified by Phelan and Link (2015)—power, prestige, beneficial social connections, and freedom (or a lack thereof), described in detail in previous sections. To test whether these mechanisms explain the rate of black LBW or the black-white ratio of LBW, I select various demographic and spatial characteristics for each MSA from the 2015 ACS 5-year estimates.

Based on the available variables in the ACS as well as the aforementioned partial theoretical overlap between evaluations of *prestige* and *power*, I combine the two concepts here

and measure the combined effect of power and prestige in five ways. First, I measure the black-white gap in occupational attainment (a proxy for the prestige and power of a given occupation) based on the percentage of each racial group in managerial positions<sup>3</sup>. For each racial group, I divide the number of workers in managerial positions by the total number of workers age 16 or older. I then divide the rate of black managerial workers by the rate of white managerial workers. Second, I measure the black-white gap in median household income. As was the case with occupational prestige, I construct race-specific median household incomes for each group before dividing the median household income for black individuals by the median household income for white individuals. Third, I measure the black-white gap in educational attainment by calculating the proportion of each racial group aged 25 years or more with a bachelor's degree or higher, then divide the proportion of black individuals with a bachelor's degree or higher by the proportion of white individuals with a bachelor's degree or higher. Fourth, I measure the black-white gap in unemployment by calculating the proportion of each racial group between the ages of 16 and 64<sup>4</sup> that are currently unemployed and dividing the proportion of black individuals who are unemployed by the proportion of whites who are unemployed. Lastly, I measure the black-white gap in poverty by calculating the proportion of each racial group with incomes below 100 percent of the Federal Poverty Line (FPL) and dividing the proportion of black individuals living in poverty by the proportion of white individuals living in poverty.

I measure *beneficial social connections* as the degree of racial and socioeconomic isolation at the MSA-level. As noted above, measures of isolation intend to capture the

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<sup>3</sup> Given the variables available from the ACS, I am unable to include measures of the percent of each racial group in a given industry, such as professional, scientific, management, and administrative and waste management services.

<sup>4</sup> Public-use ACS estimates only provide employment estimates for each racial group in two age categories: 16 to 64 and 65 or older.

probability that minority group members are only exposed to one another. If racial minorities are isolated, particularly if they are isolated in economically disadvantaged communities, they may have less contact with people who are economically and socially beneficial to them. Using spatial and tract-level demographic data available through the US Census, I calculate Lieberman's (1981) isolation index,  $xP^*_x$ , for each MSA. The isolation index is computed as the minority-weighted average of the minority proportion in each area. The isolation index ranges from 0 (minorities are completely “integrated,” exposed only to whites) to 1.0 (minorities are completely “isolated,” or exposed only to one another). The same calculations and interpretations apply for poverty isolation: the degree to which individuals earning incomes below the FPL are isolated from individuals earning incomes above the FPL. Including both measures of isolation is important not only theoretically but empirically as well given that the current body of research on racial and poverty isolation and LBW is inconsistent. In addition, while the isolation index is asymmetric and influenced by the composition of an area, it is recommended by Massey and Denton (1988) for analysis and is consistent with previous research on residential segregation and LBW. For each continuous measure of isolation, as isolation increases, access to beneficial social connections is theorized to diminish.

Lastly, I measure *freedom*, or a lack thereof, in three ways. First, I use gender ratios by race and age to capture the population removal of black men due to incarceration (Pettit and Western 2004). I measure gender ratios by dividing the sum of black women between the ages of 15 and 34 by the sum of black men between the ages of 15 and 34 for each MSA. When this ratio is below 1, there are more young black men than young black in each MSA. When this ratio is above 1, the opposite is true. A ratio of more than one implies that a meaningful percentage of

the black male population has been removed, potentially due to incarceration (Western and Wildeman 2009).

Second, I measure the degree of racial clustering within MSAs. This measure is intended to capture legacies and contemporary manifestations of housing discrimination. Using geographic boundary files and tract-level demographic data from the ACS, I measure racial clustering using White's (1983) index of spatial proximity (SP). The spatial proximity index is computed as the average of intragroup proximities for the minority and majority populations, weighted by the proportions each group represents of the total population while considering the distance between tracts (Hong et al. 2014). An SP of 1 indicates no clustering while an SP of more than 1 indicates clustering: blacks are more likely to live near one another than to live near whites. While rare, an SP of less than 1 indicates that black and white residents are more likely to live near one another than to live near members of their own racial group.

Third, I measure unfreedom using data from the Incarceration Trends dataset from the Vera Institute of Justice. The Incarceration Trends dataset includes jail population and prison statistics from 1970-2015 for each of the approximately 3,000 counties in the US that use a county jail. For this analysis, I use the average daily jail population (ADP) for black and white individuals held in jail for the years 2011 to 2015. To calculate the black-white jail population gap for each MSA, I first calculate the average black and white jail population for each county across the five years of interest. Next, I calculate the total black and white jail population within each MSA by summing the county averages. I then divide the total jail population for each racial

group by the total population within each MSA<sup>5</sup>. Finally, I divide the proportional black ADP by the proportional white ADP, producing the final measure used in regression analyses.

#### 2.3.4 Additional Controls

I control for the following additional demographic characteristics at the MSA-level: the total population, the proportion of the population that is female, the proportion of the population that is Hispanic/Latinx, and the proportion of the population that is foreign born. I include the last two controls in this list because ACS estimates do not allow for disaggregation of the Hispanic/Latinx black population or the foreign-born black population. Since the economic and social experiences of Afro-Latinx and foreign-born black residents may differ from those of US-born, non-Hispanic/Latinx black Americans, I include these covariates. In models predicting the black LBW rate, I control for the white LBW rate as well to account for the risk factors for LBW that black and white mothers potentially share (e.g., exposures to pollutants, absolute access to prenatal care). Given that key predictors such as racial isolation and clustering were calculated based on the share of the population that is black, controls for the proportion of the population that is black were not included due to multicollinearity.

#### 2.3.5 Additional Exclusion Criteria and Final Analytic Sample

The exclusion criteria applied to the natality data produced a sample of 331 MSAs from which the dependent variables were constructed. Since the ACS produces population estimates for all MSAs, there are no missing data for key independent variables. However, since segregation measures calculated from the ACS are more reliable and less uncertain in areas with

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<sup>5</sup> Since the Incarceration Trends Dataset does not disaggregate their data on jail admissions by both race and age, I am unable to ADP measures for certain age groups that may be at an elevated risk for incarceration (e.g., 15-34).

larger minority populations, I followed the convention of other studies and restricted the analyses to MSAs with at least 4,000 black residents (Napierla and Denton 2017). As such, my sample of MSAs decreases from 331 to 301. Descriptive statistics for this final set of MSAs are shown in Table 2.2.

### 2.3.6. Analysis

To investigate the effects of power, prestige, beneficial social connections, and unfreedom on the rate of black LBW and the black-white LBW ratio at the MSA-level, I ran a series of generalized linear models, assuming a normal distribution for the outcomes. The analysis and presentation of results will proceed as follows. First, I estimate the effects of each fundamental cause mechanism separately. I begin with models testing the effects of power and prestige on both outcomes: the black LBW rate and the black-white LBW gap. I then move on to the effects of beneficial social connections, followed by unfreedom. To test the independent effects of these mechanisms, I begin by estimating the bivariate associations between each measure and both outcomes. For example, in the power and prestige models, I test the effects of the black-white gap in occupational prestige, household income, BA attainment, unemployment, and poverty separately to examine the gross effects of each measure on the outcomes (see Appendix 2.A for regression analysis that include each separate FCT mechanism and controls). Next, I introduce each measure across sequential models until all five measures of power and prestige have been accounted for. Then, I introduce the MSA-level demographic controls and, for the models estimating the rate of LBW among black infants, the white LBW rate. I then repeat this process for the remaining mechanisms, beneficial social connections and unfreedom. In addition, since these mechanisms do not exist in isolation of one another, I test the additive effects of the four fundamental cause mechanisms on the outcomes. I also introduce the

mechanisms consecutively across a series of models, introducing the power and prestige measures first, followed by the measures of beneficial social connections, and ending with measures of unfreedom. Lastly, I introduce the demographic controls into these fully adjusted models.

## 2.4 Results

### 2.4.1 Power and Prestige

Research on the social determinants of LBW would suggest that as power and prestige among African Americans increases, the rate of LBW among black infants and the black-white gap in LBW will decrease. For the five measures of power and prestige included in this analysis, we would expect to see a negative association between the black-white gap in occupational prestige, household income, and BA attainment and both outcomes. That is, as the occupational, economic, and educational standings of African Americans in a given MSA improves, so does black infant health. Likewise, we would expect to see a positive association between the black-white gap in poverty and unemployment and both LBW outcomes, as an increase in these predictors implies a lower level of power and prestige among African Americans.

The results presented in Tables 2.3 and 2.4 suggest that these expectations hold true in the models testing the bivariate association between the five measures of power and prestige and the rate of black LBW and black-white gap in LBW, respectively. For both outcomes, as the occupational prestige, household income, and BA attainment of African Americans in an MSA improves, the black LBW rate decreases and the black-white gap in LBW narrows. The converse is true for the black-white gap poverty and unemployment, as the result of the bivariate models show a positive association. For both outcomes, the associations for household income, BA attainment, and unemployment are statistically significant. In addition, the associations between

the black-white poverty rate and both outcomes do not reach statistical significance. However, the black-white gap in occupational prestige seems to be operating differently across outcomes in these bivariate models, as the association between occupational prestige and the black LBW rate is negative and statistically significant while the association between occupational prestige and the black-white gap in LBW is negative but not statistically significant. This implies that, independent of additional covariates, the inequality in occupational standing among black and white MSA residents may have no effect on the inequality in LBW between black and white infants but seems to have a meaningful relationship to the proportion of black infants that are born LBW. To see if these associations hold when all measures of power and prestige are introduced, I turn to the results in Tables 2.5 and 2.6.

Table 2.5 presents a series of models predicting the black LBW rate. Looking first at models 1-4, the results show that when all five measures of power and prestige are introduced into the model, only household income, BA attainment, and unemployment remain statistically significant and in the expected direction. However, the black-white gap in occupational prestige is no longer statistically significant and the association is now positive. In addition, the black-white gap in poverty remains statistically significant in the fully adjusted model (Model 4), but the sign has reversed. These results would imply that an increase in occupational prestige and a decrease in the poverty rate among African Americans *increases* the black LBW rate, contradicting the expectation that improved levels of power and prestige would improve health as well. However, a likely explanation for these contradictory findings is that the positive effects of occupational standing and the negative effects of poverty have been fully captured by the other measures included in the full model. Indeed, comparing model fit statistics (i.e., the Akaike Information Criterion) implies that once occupational prestige and income have been accounted

for, the other variables don't greatly improve the explanatory power of the model. Concerns about the relative importance of predictor variables in this and other models, as well as issues of multicollinearity and potential methods for data reduction will be noted in subsequent sections (see Appendix 2.A for the correlation matrix for key independent variables).

Table 2.5 also includes results for the associations between each measure of power and prestige and the black LBW rate once demographic controls have been introduced. As Model 5 shows, once these population characteristics are accounted for, the associations for household income, BA attainment, and unemployment remain statistically significant and in the expected direction. Additionally, the associations for occupational prestige and poverty are still in the opposite direction as expected and statistically significant. In Model 6, the association between the white LBW rate and the outcome are statistically significant, net of the other covariates in the model. This result implies that there are mechanisms not directly observed in this model that increase the likelihood of LBW among black and white mothers in an MSA. Model 6 also shows that the increased shares of the female and Hispanic populations in an MSA increases the black LBW rate, while increased shares of the foreign-born population is protective.

Turning to the models predicting the black-white gap in LBW, I find a similar pattern. In Table 2.6, the results show that once all measures of power and prestige are introduced in Model 4, the associations for household income, BA attainment, and unemployment remain statistically significant and in the expected direction. Likewise, the associations for occupational prestige and poverty are also statistically significant but are in the opposite direction as we would expect. While the association between the black-white gap in poverty and the black LBW rate was statistically significant, the association between the black-white gap in poverty and LBW is not statistically significant once demographic controls are introduced. In addition, whereas several

demographic characteristics of MSAs had statistically significant associations with the black LBW rate, these same characteristics have no statistically significant association with the black-white gap in LBW.

#### 2.4.2 Beneficial Social Connections

As noted in previous sections, research on the relationship between racial and poverty isolation and LBW has been somewhat inconclusive. The current study builds on this body of research and at present, is the largest analysis of birth outcomes across MSAs, including over 70 more MSAs than previous analyses (Bell et al. 2006; Walton 2009). Based on prior research, I expect the associations for both racial and poverty isolation in an MSA to be positively associated with both LBW outcomes: as racial and poverty isolation increase, so does the black LBW rate and the black-white gap in LBW. It is also plausible, based on previous research, that the effects of racial isolation on LBW will be greatest in MSAs that also have high levels of poverty isolation (see Appendix 2.A for models with interaction terms).

Table 2.7 presents a series of models estimating the associations between diminished access to beneficial social connections and the black LBW rate. Results in Models 1 and 2 indicate that as African Americans become more racially isolated and as low-income households become more economically isolated, the black LBW rate increases. When both measures are included in Model 3, the associations with the outcome are attenuated somewhat, but the results suggest that racial and poverty isolation have separate, statistically significant associations with the black LBW rate. Even once demographic characteristics and the white LBW rate are introduced in Models 4 and 5, the associations remain. A similar series of model estimates presented in Table 2.8 show the associations between racial and poverty isolation and the black-white LBW gap. Comparing the results in Table 2.8 to those in Table 2.7, it is clear that both

racial and poverty isolation have independent and substantial associations with both the black LBW rate and the black-white gap in LBW even once common demographic confounders are accounted for.

### 2.4.3 Unfreedom

Lastly, I examine the associations between three measures of unfreedom and both outcomes. The measures of unfreedom included in this analysis, racial clustering, gender ratios, and the black-white gap in jail populations, are intended to capture aggregate levels of unfreedom among the black population in a given MSA. As noted in previous sections, the body of research on these circumstances and LBW is minimal. Of the studies that have included racial clustering in their analysis, the findings have been inconsistent. It is possible that racial clustering reflects legacies of housing discrimination and exposure to neighborhood disadvantage, but it is also plausible that residents in these communities build supportive social networks that serve as protective factors. Additionally, while no studies have explicitly examined the relationship between gender imbalances and LBW, if these gender ratios reflect the population removal of young black men due to incarceration or death, it is likely that this expulsion will have a negative effect on the health of community members, including black women and their children. Likewise, given that previous research has shown that measures of incarceration have negative health consequences for birth outcomes, I expect that as the black-white jail population gap increases, the black LBW rate will also increase and the black-white gap in LBW will widen.

Models estimating the association between unfreedom and the black LBW rate are shown in Table 2.9. In the bivariate models, I find that racial clustering and gender ratios at the MSA-level both have statistically significant, positive associations with the rate of black LBW. As

clustering increases, so does the black LBW rate. Likewise, as the number of black women aged 15-34 begins to outweigh the number of black men of the same age, the black LBW rate increases. For the black-white gap in jail populations, the association is statistically significant and negative. This finding contradicts theoretical expectations for the association between incarceration and health and implies that as the black jail population increases relative to the white jail population, the rate of black LBW decreases. However, when all three measures of unfreedom are included in Model 5, I find that only the black gender ratio variable has a statistically significant association with the outcome and that both the size and the magnitude of the associations between the other measures of unfreedom and the black LBW rate have been attenuated. This pattern holds when demographic characteristics and the white LBW rate are introduced in subsequent models.

Table 2.10 presents the results for models predicting the black-white LBW gap. As was the case with models predicting the black LBW rate, the bivariate models shown in Table 2.10 suggest that as gender ratios become more skewed, the black-white LBW gap widens. However, the bivariate models in Table 2.10 show null associations for both racial clustering and the black-white jail population gap. As was also the case for the black LBW rate outcome, when all three measures of unfreedom are introduced and demographic characteristics are accounted for, only the black gender ratio has a statistically significant association with the black-white gap in LBW.

#### 2.4.4 Racism as a Fundamental Cause of LBW

I now turn to a series of models that include all of the mechanisms: power, prestige, beneficial social connections, and unfreedom. In these final models, I introduce each fundamental cause mechanism consecutively across four models. Since models estimating the effects of power and prestige on the outcomes have already been presented and described, the

first model includes measures for power, prestige, and beneficial social connections. The second model introduces measures for unfreedom. Lastly, I introduce the demographic characteristics of the MSA. In addition, I estimate a fourth model for the black LBW rate, which includes the white LBW rate as a covariate as well.

Results predicting the black LBW rate are shown in Table 2.11. In Model 1, I find that when racial and poverty isolation are introduced, the associations of each measure of power and prestige are reduced in size and statistical significance. In fact, only the association between the black-white gap in poverty and the black LBW rate remain statistically significant once racial and poverty isolation are accounted for. In contrast, Model 4 in Table 2.6 suggests statistically significant associations between each measure of power and prestige and the outcomes. This shift implies that the benefits of greater power and prestige among African Americans in an MSA is partially realized through the degree to which these beneficial social actors are evenly distributed throughout the metropolitan area. If black residents are still more likely to experience racial and poverty isolation, the benefits of improved economic and social standing are partially or fully mitigated.

Adding measures of unfreedom into Model 2 supports this notion further. In this model, none of the five measures of prestige and power have a statistically significant association with the outcome. In addition, while the association for poverty isolation remains relatively unchanged, the association for racial isolation increases in size. Furthermore, the association between racial clustering and the outcome is negative and statistically significant while the association for the two other measures of unfreedom are null. As such, it appears that the effects of residential segregation on the black LBW rate can be split into two competing forces: the detrimental effects of racial isolation, and the potentially mitigating effects of racial clustering.

Model 3 introduces controls for population characteristics, producing several differences in comparison to Model 2. For measures of power and prestige, the association for the black-white gap in occupational prestige is statistically significant and positive while the association for the black-white gap in educational attainment is statistically significant and negative. All other measures of power and prestige have a null association with the outcome. For the remaining fundamental cause mechanisms, only racial isolation as a proxy for beneficial social connections remains statistically significant in Model 3. Model 4 introduces a final control for the white LBW rate. In this final model, the associations for the black-white gap in occupational prestige, the black-white gap in BA attainment, and racial isolation remain unchanged from Model 3. In addition, the association for poverty isolation is once again positive and statistically significant while the association for racial clustering is negative a statistically significant.

The results for models predicting the black-white LBW gap are shown in Table 2.12. In the first model, I find that as was the case with the black LBW rate, the black-white occupational prestige gap has a positive and statistically significant association with the outcome and the black-white gap in BA attainment has a negative and statistically significant association. In contrast to the black LBW rate models, the black-white gap in unemployment is a positive and statistically significant predictor of the black-white gap in LBW. In addition, whereas racial isolation was a robust predictor of the black LBW, that is not the case here. Instead, poverty isolation has a positive and statistically significant association with the outcome.

In Model 2, I introduce controls for unfreedom and find that, in contrast to the findings for the rate of black LBW, the black gender ratio has a statistically significant, positive relationship with the outcome while racial clustering has a negative but not statistically significant association. In addition, once these measures are introduced, the association for

poverty isolation is reduced in size and statistical significance, again implying that residents in racially clustered communities may also have access to other social networks and resources that buffer the negative effects of isolation. As for the measures of power and prestige in Model 2, the associations with the outcome remain largely unchanged once measures of unfreedom are introduced. Lastly, Model 3 introduces demographic characteristics of each MSA but the results remain largely unchanged and only the share of the population that is foreign-born is a significant demographic predictor for the black-white LBW gap.

#### 2.4.5 Exploratory Factor Analysis

This analysis uses FCT as a framework to investigate the structural manifestations of racism within MSAs and the effects of these manifestations on a specific health outcome: LBW. While FCT is often cited in health research, the theory is not often directly applied in empirical analyses. In addition, FCT has been the subject of much debate, critique, and some revisions since its original articulation (Link and Phelan 1995; Lutfey and Freese 2005; Freese and Lutfey 2011). As such, the secondary goals of this analysis are to determine if the measures included here accurately capture the four race-specific flexible resources identified by Phelan and Link (2015). While the predictors used to measure each FCT mechanism were chosen based on theoretical relevance and findings from previous research, model fit statistics and the results of the fully adjusted models in Tables 2.11 and 2.12 suggest that the relative contribution of each predictor may be obscured.

To address this, I perform three methodological tests. First, I compute multicollinearity statistics for the power and prestige predictors. I find that while there is evidence of collinearity, which should be expected for measures intended to capture the same concept, the variance inflation factor (VIF) and Tolerance statistics suggest that there is no need to adjust or remove

any of the five measures. Second, I compute the incremental  $R^2$  for the first four models presented in Table 2.5. The results of this supplemental analysis suggests that the black-white gap in occupational prestige, household income, and poverty suffice to capture the association between power and prestige and the black LBW rate. Still, educational attainment and unemployment may capture unique aspects of racial differences in power and prestige. As noted in the review, black workers experience a greater degree of occupational mismatch based on credentials and higher rates of discrimination in higher and firing. As such, it may be worthwhile to keep these predictors in the model. To account for this, I use factor analysis to explore the possibility of combining these measures into a single index.

Factor analysis is a dimension reduction technique used to explain the shared variance among predictors and is based on the theoretical assumption of a latent variable that can't be measured directly but that is causing observations to manifest in a similar way across a set of variables. This theoretical assumption fits the underlying structure of FCT. Through parallel analysis and other exploratory techniques, I determine that the ten FCT measures included in the analysis load onto two latent factors. During this exploratory phase I also determine that the black-white jail population gap cannot be represented by one of these two factors. As such, I do not include this predictor in the analysis. I retain two latent factors using an orthogonal varimax rotation which assumes that separate variables do not load onto two factors<sup>6</sup>. The variables used to measure power and prestige loaded onto a single factor, which I continue to refer to as “power and prestige”<sup>7</sup>, while the remaining covariates (racial isolation, poverty isolation, black gender

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<sup>6</sup> While factor analysis is theoretically aligned with FCT and thus presented here, principal components analysis produces similar component loadings.

<sup>7</sup> In creating this factor, I rescaled the black-white unemployment and poverty gaps such that an increase in both metrics represented an increase in the socioeconomic standing of African Americans relative to whites.

ratios, and racial clustering) loaded onto a second factor, which I refer to as “spatial disadvantage”. These final loadings were then used to weight each variable’s contribution and extracted as standardized indices for regression analysis. The association between each factor, demographic controls, and both the black LBW rate and the black-white gap in LBW are shown in Table 2.13.

As shown in Table 2.13, as black power and prestige increases, the black LBW rate and the black-white gap in LBW decreases. This is expected as an increase in power and prestige implies that black residents in a given MSA have higher levels of occupation attainment, household income, educational attainment, and employment as well as lower levels of poverty. As the overall socioeconomic standing of black residents improves, we would expect that the health of black infants improves as well. For both outcomes, this association is statistically significant at the 0.001 alpha level. The second factor, spatial disadvantage, has a positive association with both outcomes and is also statistically significant. That is, MSAs with higher levels of racial isolation, poverty isolation, racial clustering, and greater gender imbalances among young African Americans also have higher rates of black LBW and wider black-white gaps in LBW.

These supplemental analyses suggest that the five measures of power and prestige included here can be used to create a single index. The analysis also implies that the associations between this index and LBW align with the assumptions of FCT. However, results from the factor analysis suggest that racial isolation, poverty isolation, racial clustering, and the black gender ratio measures are the manifestation of a single latent construct, rather than two separate concepts (e.g., beneficial social connections and unfreedom). This confluence is likely due to the use of racial clustering as a measure of unfreedom. Racial clustering is a measure of racial

segregation intended to capture the extent to which contiguous neighborhoods share similar aggregate characteristics (e.g., racial composition). Perhaps unsurprisingly, this measure is highly correlated with the measure of residential racial isolation intended to capture access to beneficial social connections ( $r = 0.717$  for the final analytic sample). While previous analyses have included both measures (Bell et al. 2006, Walton 2009), the results of the factor analysis suggest that these two measures may not capture distinct processes. However, the results by Bell et al. (2006) as well as the findings presented here suggest that racial isolation and racial clustering have distinct relationships with LBW. As such, it may be worthwhile to include both measures in analyses in an effort to identify the potential mitigating effects of resilient communities that are racially clustered. In addition, the use of other data sources such as the Home Mortgage Disclosure Act (HMDA) to construct measures of redlining (Mendez et al. 2014, Gee 2002) may more accurately capture legacies of housing discrimination and unfreedom.

Finally, the remaining measures of unfreedom included here do not seem to fully capture this concept. The black gender ratio measure has been used in previous research as a proxy for the demographic consequences of mass incarceration, but does not seem to capture a process distinct from the measures of racial and economic segregation used in this analysis. Likewise, the measure of racial disparities in the jail population for a given MSA does not load onto a single factor nor does it show a meaningful association with either outcome. This latter result is surprising, considering that previous research has found associations between aggregate measures of mass incarceration and infant health (Wildeman 2012). However, this analysis differs from previous research in several ways. First, previous research has investigated the associations between state-level measures of imprisonment and infant mortality while the

analyses presented here investigate the association between MSA-level measures of jail populations and LBW. As such, the level of aggregation used in this analysis may be inappropriate for estimating the associations between incarceration and infant health. An immediate next step for analysis would be to investigate state or county level associations between racial disparities in the jail population and LBW. Additionally, while the distal mechanisms that lead to differences in jail admission and prison admission may be similar, these processes may be distinct enough to produce different associations with infant health. Likewise, while LBW and infant mortality may have similar etiologies, their risk profiles may differ in such a way that results are not equivalent across outcomes. While future research should seek to identify these processes further, the evidence presented here suggests that FCT is a useful framework for racial disparities in LBW.

## 2.5 Discussion and Conclusion

The goal of this analysis was to investigate the association between structural manifestations of racial inequality in MSAs and the black-white disparity in LBW, using FCT as a guiding theoretical framework. Based on the analyses presented above, it appears that power, prestige, beneficial social connections, and unfreedom do help explain patterns in LBW at the MSA level, but that these mechanisms operate somewhat differently depending on whether the outcome of interest is the black LBW rate or the gap in LBW between black and white infants. It is important to note that when predicting the black LBW rate, the independent variables are only showing associations with black infant births at the MSA level. However, when predicting the black-white gap in LBW, the models are showing not only how the independent variables correspond with black infant health but white infant health as well. As such, a predictor can decrease the gap in LBW between babies born to black and white mothers solely by increasing

the likelihood that white babies are born LBW with no corresponding change in the likelihood that black babies are born LBW.

For the relationship between the four fundamental cause mechanisms and the black LBW rate, I can draw several conclusions. First, for measures of power and prestige, MSAs in which African Americans have achieved higher levels of BA attainment relative to whites correspond with a lower likelihood of LBW among black infants. The effects of the black-white gaps in income, poverty, and unemployment are not statistically significant in the fully-adjusted models, implying that differences in these predictors across MSAs has no association with the black LBW rate based on the model specifications. The relationship between the black-white gap in occupational prestige and the black LBW rate presents a contradiction and implies that when other measures of power and prestige are accounted for, higher levels of occupational attainment among African Americans corresponds to higher rates of LBW for babies born to black mothers. However, exploratory factor analyses suggest that this contradictory finding is an artifact of the association between covariates and that these predictors can be reduced to a single factor that captures MSA-level differences in power and prestige between black and white residents. Results of the factor analysis suggest that increases in power and prestige correspond to a decrease in the black LBW rate at the MSA level.

The black-white gaps in occupational prestige and BA attainment operates similarly for the black-white gap in LBW, implying that higher levels of these predictors correspond to a widening gap in LBW because of changes in the black LBW rate, not the white LBW rate. However, the association between the black-white gap in unemployment and the black-white gap in LBW is statistically significant in the fully adjusted models. This association was not statistically significant for the fully-adjusted model predicting the black LBW rate, implying that

as the share of black MSA residents experience unemployment increases relative to the share of white residents experiencing unemployment there are corresponding decreases in the white LBW rate rather than increases in the black LBW rate. However, it is worth noting that if I assume a one-tailed hypothesis test for the association between the black-white unemployment gap and the black LBW rate in a given MSA, the association is statistically significant at the 0.05 alpha level. As such, racial differences in unemployment have a probable association with both the black LBW rate and the black-white gap in LBW.

For the black LBW rate, both racial and poverty isolation have positive, statistically significant associations with the outcome. As racial isolation increases, so does the black LBW rate. The same is true for poverty isolation. This is true even when measures of power and prestige are accounted for, implying that patterns of residential segregation in an MSA may influence the likelihood of LBW through mechanisms other than black-white gap in SES. Potential mechanisms contributing to the association between racial and poverty isolation and LBW may include diffusion of harmful health behaviors, exposure to crime and violence, poor housing conditions, and exposure to environmental toxins. While both measures of isolation have a statistically significant association with the black LBW rate, this is not true for the black-white gap in LBW. This difference implies that while racial and poverty isolation is detrimental to black infant health, either it is not consequential enough to correspond with wider gaps in LBW or there are similar detrimental effects on the health of white infants.

The measures of unfreedom included in this analysis also appear to be operating differently across outcomes. For the black gender ratio measures, a proxy for the population removal of young black men in a given MSA due to incarceration, I find no association with the black LBW rate across models in Table 2.11. However, I do find a positive and statistically

significant association between this measure and the black-white gap in LBW. This difference would imply that as the gender imbalance between young black women and young black men in an MSA increases, the white LBW rate decreases, widening the gap in LBW between black and white infants. However, as was the case with the results for the association between the black-white unemployment gap and black LBW rate, a directional test of the association would produce a statistically significant association between the black gender ratio and the black LBW rate. As such, gender imbalances among young black men and women correspond with an increase in the black LBW rate as well as increases in the black-white LBW gap.

The second measure of unfreedom included in this analysis, racial clustering, has a protective association with the black LWB rate. While this finding may seem unexpected based on the assumption that racial clustering indicates housing discrimination and exposure to neighborhood disadvantage, this finding is supported by other analyses showing that racial clustering corresponds with improved black infant health (Bell et al. 2006). As noted in previous sections, researchers hypothesize that African Americans who live in clustering or concentrated communities buffer the negative health consequences of residential segregation through access to social networks that improve physical and mental health. An important avenue for future research would be to investigate these micro-level processes of resilience in marginalized communities. Still, in the fully adjusted models predicting the black-white LBW gap, racial clustering has a negative association with the outcome, but the association is not statistically significant. Therefore, while racial clustering may be protective for the risk of LBW among black infants, it is not beneficial enough to minimize the gap in LBW between babies born to black and white mothers within MSAs.

The final measure of unfreedom included in this analysis, the black-white jail population gap, has small and not statistically significant associations with both outcomes. While this results contradicts expectations that black-white disparities in jail populations will correspond with increases in the black LBW rate and the black-white LBW ratio, it may be the case that this measure does not accurately capture the concept of “unfreedom”, that this is not a type of unfreedom that matters for the outcome, that the association between this measure at the outcomes are fully explained by other covariates in the model, or that the MSA is not an appropriate level of aggregation to accurately capture the detrimental effects of greater black incarceration on LBW. In addition, results from the confirmatory factor analysis suggests that the black-white jail population gap does not load onto one of the two latent factors captured by the other predictors in the model.

Fundamental cause theory has been a primary theoretical framework in social epidemiology for almost 25 years. FCT urges researchers to look “upstream”, to the social conditions that put individuals and populations at “risk of risks”. Using aggregated measures of racial differences in power, prestige, beneficial social connections, and freedom, this analysis suggests that FCT is a useful framework for investigating the association between aggregate level measures of racial inequality and health. However, model fit statistics suggest that the measures of each FCT mechanism included here, as well as relevant population characteristics, do not fully explain the variation in the black LBW rate and the black-white LBW ratio across MSAs. That is, these measures do not fully capture the social conditions that put black mothers at “risk of risks”. In the next empirical chapter, I investigate this possibility by identifying MSAs with higher or lower rates of black LBW and/or larger or smaller black-white gaps in LBW than we would expect based on racial inequalities in each FCT mechanism.

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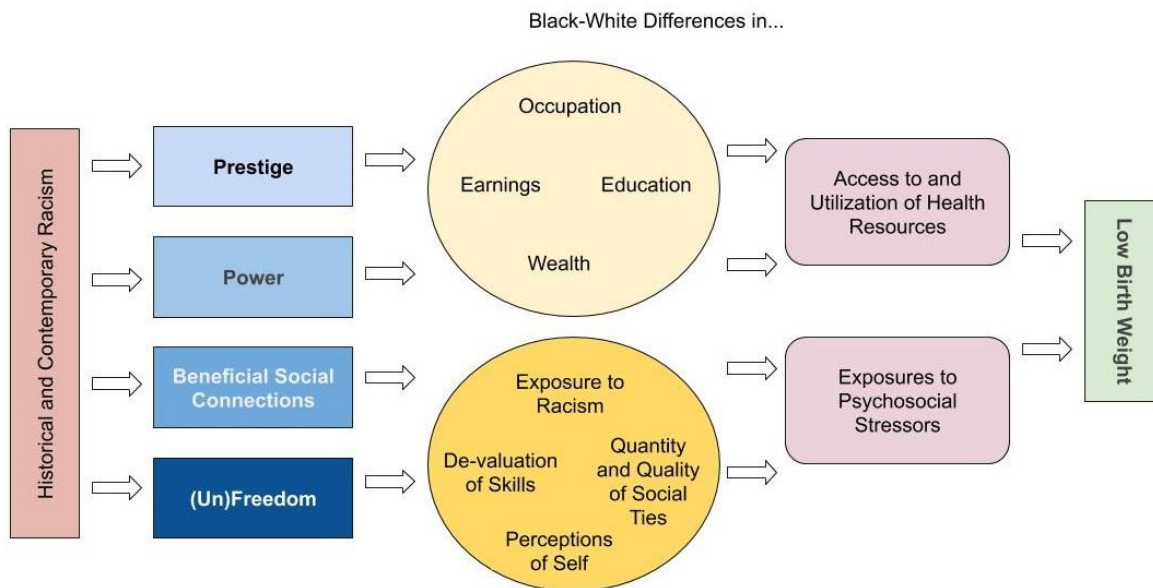


Figure 2.1. Conceptual Model of Racism as a Fundamental Cause of Black-White Disparities in LBW

**Table 2.1. Natality Data Sample Restrictions**

<i>Restriction Applied</i>	2013	2014	2015	2016	Total
Full Sample	3.94	4.00	3.99	3.96	15.89
Non-Hispanic Black and Non-Hispanic White Mothers	2.71	2.74	2.72	2.68	10.85
Singleton Births	2.61	2.63	2.62	2.58	10.44
37-42 Weeks Gestation	2.28	2.30	2.29	2.25	9.12
500 to 6000 grams Birth Weight	2.28	2.30	2.29	2.25	9.12
Occurred in an MSA (excludes Puerto Rico)	2.00	2.02	2.02	1.99	8.03
100 or more Births to NH Black and NH White Mothers across All Years (MSAs = 331)	-	-	-	-	7.84

*Note: All sample sizes are in millions.*

**Table 2.2. Descriptive Statistics and Data Sources for Analytic Sample**

Variable	Measurement	Data Source	Mean	Std. Dev	Min	Max
<i>Dependent Variables</i>						
Black-White LBW Ratio	$\frac{\text{Black LBW Rate}}{\text{White LBW Rate}}$	NVSS Natality File 2013-2016	2.13	0.55	0.74	5.66
Black LBW Rate	$\frac{\text{Number of LBW Births to Black Mothers}}{\text{Total Number of Births to Black Mothers}}$	NVSS Natality File 2013-2016	0.05	0.01	0.01	0.09
<i>Covariates</i>						
White LBW Rate	$\frac{\text{Number of LBW Births to White Mothers}}{\text{Total Number of Births to White Mothers}}$	NVSS Natality File 2013-2016	0.02	0.01	0.01	0.04
Population (in millions)		ACS 5-year estimates 2015	0.85	1.80	0.08	19.98
Log (Total Population)		ACS 5-year estimates 2015	12.87	1.09	11.3	16.8
Proportion Female Population	$\frac{\text{Number of Female Residents}}{\text{Total Population}}$	ACS 5-year estimates 2015	0.51	0.01	0.44	0.53
Proportion Hispanic Population	$\frac{\text{Number of Hispanic Residents}}{\text{Total Population}}$	ACS 5-year estimates 2015	0.12	0.12	0.01	0.81
Proportion Foreign-born	$\frac{\text{Number of Foreign – born Residents}}{\text{Total Population}}$	ACS 5-year estimates 2015	0.08	0.07	0.01	0.39
<i>Power &amp; Prestige</i>						
Black-White Occupational Prestige Ratio	$\frac{\frac{\text{Number of black workers 16 and older in managerial positions}}{\text{Total number of black workers 16 and older}}}{\frac{\text{Number of white workers 16 and older in managerial positions}}{\text{Total number of white workers 16 and older}}}$	ACS 5-year estimates 2015	0.71	0.16	0.30	1.34
Black-White HH Income Ratio	$\frac{\text{Black Median Household Income}}{\text{White Median Household Income}}$	ACS 5-year estimates 2015	0.60	0.14	0.34	1.45

Black-White BA Ratio	$\frac{\frac{\text{Number of black residents 25 and older with a bachelor's degree}}{\text{Total number of black residents 25 and older}}}{\frac{\text{Number of white residents 25 and older with a bachelor's degree}}{\text{Total number of white residents 25 and older}}}$	ACS 5-year estimates 2015	0.60	0.19	0.24	1.60
Black-White Unemployment Ratio	$\frac{\frac{\text{Number of black residents aged 16 – 64 who are currently unemployed}}{\text{Total number of black residents aged 16 – 64}}}{\frac{\text{Number of white residents aged 16 – 64 who are currently unemployed}}{\text{Total number of white residents aged 16 – 64}}}$	ACS 5-year estimates 2015	2.11	0.60	0.51	5.22
Black-White Poverty Ratio	$\frac{\frac{\text{Number of black residents in poverty}}{\text{Total number of black residents}}}{\frac{\text{Number of white residents in poverty}}{\text{Total number of white residents}}}$	ACS 5-year estimates 2015	2.43	0.75	0.70	5.36

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*Beneficial Social Connections*

Racial Isolation	$\sum_{i=1}^n \left[ \left( \frac{\text{Black population in census tract}}{\text{Black population in MSA}} \right) \left( \frac{\text{Black population in census tract}}{\text{Total population in census tract}} \right) \right]$	ACS 5-year estimates 2015	0.27	0.18	0.03	0.71
Poverty Isolation	$\sum_{i=1}^n \left[ \left( \frac{\text{Population in poverty in census tract}}{\text{Population in poverty in MSA}} \right) \left( \frac{\text{Population in poverty in census tract}}{\text{Total population in census tract}} \right) \right]$	ACS 5-year estimates 2015	0.23	0.05	0.11	0.38

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*(Un)Freedom*

Black Gender Ratio 15-34	$\frac{\text{Black women aged 15 – 34}}{\text{Black men aged 15 – 34}}$	ACS 5-year estimates 2015	0.94	0.20	0.31	1.27
Racial Clustering	<i>Index of Spatial Proximity (SP<sup>a</sup>)</i>	ACS 5-year estimates 2015	1.20	0.21	0.99	1.96
Black-White Jail Gap	$\frac{\frac{\text{Black average daily jail population}}{\text{Total number of black residents}}}{\frac{\text{White average daily jail population}}{\text{Total number of white residents}}}$	VERA Incarceration Trends Dataset 2011-2015	6.16	4.18	0.53	49.36

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*N = 301*

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<sup>a</sup>See [https://www.census.gov/hhes/www/housing/resse/pdf/app\\_b.pdf](https://www.census.gov/hhes/www/housing/resse/pdf/app_b.pdf) for measurement of the index of spatial proximity.

**Table 2.3. Bivariate Associations: Power, Prestige, and the Black LBW Rate**

	(1)	(2)	(3)	(4)	(5)
Occupational Prestige	<b>-0.0098*</b> (0.0044)				
HH Income		<b>-0.0192***</b> (0.0047)			
BA Attainment			<b>-0.0121***</b> (0.0036)		
Unemployment				<b>0.0026*</b> (0.0011)	
Poverty					0.0006 (0.0009)
Constant	0.0550*** (0.0032)	0.0596*** (0.0029)	0.0554*** (0.0023)	0.0426*** (0.0025)	0.0466*** (0.0023)
Observations	301	301	301	301	301
R <sup>2</sup>	0.0164	0.0523	0.0368	0.0166	0.0015
	-	-	-	-	-
Akaike Inf. Crit.	1,809.865 0	1,821.063 0	1,816.163 0	1,809.916 0	1,805.345 0

*Note:*

\* p&lt;0.05; \*\* p&lt;0.01; \*\*\* p&lt;0.001

**Table 2.4. Bivariate Associations: Power, Prestige, and the Black-White Gap in LBW**

	(1)	(2)	(3)	(4)	(5)
Occupational Prestige	-0.2447 (0.2020)				
HH Income		<b>-0.7074**</b> (0.2182)			
BA Attainment			<b>-0.7411***</b> (0.1617)		
Unemployment				<b>0.1941***</b> (0.0519)	
Poverty					0.0657 (0.0420)
Constant	2.2992*** (0.1466)	2.5531*** (0.1355)	2.5724*** (0.1021)	1.7164*** (0.1137)	1.9661*** (0.1066)
Observations	301	301	301	301	301
R <sup>2</sup>	0.0049	0.0340	0.0657	0.1453	0.0081
Akaike Inf. Crit.	495.9633	487.0406	476.9898	483.6768	494.9761
<i>Note:</i>	* p<0.05; ** p<0.01; *** p<0.001				

**Table 2.5. Power, Prestige, and the Black LBW Rate**

	(1)	(2)	(3)	(4)	(5)	(6)
Occupational Prestige	0.0007 (0.0053)	0.0066 (0.0063)	0.0069 (0.0063)	0.0079 (0.0062)	<b>0.0123*</b> (0.0059)	<b>0.0120*</b> (0.0053)
HH Income	<b>-0.0196***</b> (0.0058)	<b>-0.0170**</b> (0.0060)	<b>-0.0157*</b> (0.0065)	<b>-0.0309***</b> (0.0075)	<b>-0.0228**</b> (0.0069)	<b>-0.0180**</b> (0.0063)
BA Attainment		-0.0088 (0.0050)	-0.0090 (0.0050)	<b>-0.0104*</b> (0.0049)	<b>-0.0114*</b> (0.0045)	<b>-0.0163***</b> (0.0041)
Unemployment			0.0007 (0.0013)	<b>0.0028*</b> (0.0014)	0.0018 (0.0013)	<b>0.0029*</b> (0.0012)
Poverty				<b>-0.0052***</b> (0.0014)	<b>-0.0049***</b> (0.0013)	<b>-0.0034**</b> (0.0012)
Log (Total Population)					0.0002 (0.0007)	0.0002 (0.0006)
Proportion Female Population					<b>0.2911***</b> (0.0643)	<b>0.1782**</b> (0.0600)
Proportion Hispanic Population					<b>0.0210**</b> (0.0077)	<b>0.0159*</b> (0.0070)
Proportion Foreign-born					<b>-0.0858***</b> (0.0163)	<b>-0.0392*</b> (0.0159)
White LBW Rate						<b>0.8903***</b> (0.1117)
Constant	0.0594*** (0.0034)	0.0590*** (0.0034)	0.0565*** (0.0055)	0.0742*** (0.0071)	-0.0772* (0.0332)	-0.0494 (0.0303)
Observations	301	301	301	301	301	301
R <sup>2</sup>	0.0523	0.0621	0.0631	0.1079	0.2677	0.399
Akaike Inf. Crit.	-1,819.08	-1,820.17	-1,818.49	-1,831.25	-1,882.67	-1,940.30

*Note:*

\*p&lt;0.05; \*\*p&lt;0.01; \*\*\*p&lt;0.001

**Table 2.6. Power, Prestige, and the Black-White LBW Ratio**

	(1)	(2)	(3)	(4)	(5)
Occupational Prestige	0.2023 (0.2456)	<b>0.8853**</b> (0.2817)	<b>0.9632***</b> (0.2793)	<b>0.9937***</b> (0.2767)	<b>0.8023**</b> (0.2847)
HH Income	<b>-0.8372**</b> (0.2693)	<b>-0.5319*</b> (0.2695)	-0.2217 (0.2857)	<b>-0.6982*</b> (0.3342)	<b>-0.7321*</b> (0.3377)
BA Attainment		<b>-1.0216***</b> (0.2256)	<b>-1.0641***</b> (0.2232)	<b>-1.1068***</b> (0.2214)	<b>-1.0941***</b> (0.2194)
Unemployment			<b>0.1687**</b> (0.0567)	<b>0.2337***</b> (0.0612)	<b>0.2160***</b> (0.0621)
Poverty				<b>-0.1635**</b> (0.0611)	-0.1108 (0.0644)
Log (Total Population)					-0.0275 (0.0344)
Proportion Female Population					2.0951 (3.1273)
Proportion Hispanic Population					0.2514 (0.3735)
Proportion Foreign-born					1.4998 (0.7912)
Constant	2.4882*** (0.1568)	2.4351*** (0.1524)	1.8623*** (0.2444)	2.4142*** (0.3178)	1.6114 (1.6125)
Observations	301	301	301	301	301
R <sup>2</sup>	0.0361	0.0984	0.1245	0.1453	0.1749
Akaike Inf. Crit.	488.3564	470.2637	463.4035	458.1800	455.5711

Note:

\* p<0.05; \*\* p<0.01; \*\*\* p<0.001

**Table 2.7. Beneficial Social Connections and the Black LBW Rate**

	(1)	(2)	(3)	(4)	(5)
Racial Isolation	<b>0.0302</b> <sup>***</sup> (0.0035)		<b>0.0254</b> <sup>***</sup> (0.0037)	<b>0.0235</b> <sup>***</sup> (0.0042)	<b>0.0218</b> <sup>***</sup> (0.0039)
Poverty Isolation		<b>0.0801</b> <sup>***</sup> (0.0130)	<b>0.0509</b> <sup>***</sup> (0.0128)	<b>0.0382</b> <sup>**</sup> (0.0126)	<b>0.0356</b> <sup>**</sup> (0.0116)
Log (Total Population)				-0.0011 (0.0007)	-0.0009 (0.0006)
Proportion Female Population				<b>0.1903</b> <sup>**</sup> (0.0618)	<b>0.1144</b> <sup>*</sup> (0.0580)
Proportion Hispanic Population				<b>0.0239</b> <sup>***</sup> (0.0068)	<b>0.0150</b> <sup>*</sup> (0.0064)
Proportion Foreign- born				<b>-0.0661</b> <sup>***</sup> (0.0154)	<b>-0.0305</b> <sup>*</sup> (0.0151)
White LBW Rate					<b>0.7313</b> <sup>***</sup> (0.1016)
Constant	0.0398 <sup>***</sup> (0.0012)	0.0293 <sup>***</sup> (0.0031)	0.0292 <sup>***</sup> (0.0029)	-0.0470 (0.0308)	-0.0294 (0.0285)
Observations	301	301	301	301	301
R <sup>2</sup>	0.1951	0.2364	0.2355	0.3416	0.4405
Akaike Inf. Crit.	-1,870.212	-1,840.628	-1,883.726	-1,920.676	-1,967.680

*Note:*

\* p&lt;0.05; \*\* p&lt;0.01; \*\*\* p&lt;0.001

**Table 2.8. Beneficial Social Connections and the Black-White LBW Ratio**

	(1)	(2)	(3)	(4)
Racial Isolation	<b>0.6679<sup>***</sup></b> (0.1768)		<b>0.5204<sup>**</sup></b> (0.1856)	<b>0.7311<sup>**</sup></b> (0.2267)
Poverty Isolation		<b>2.1758<sup>***</sup></b> (0.6216)	<b>1.5788<sup>*</sup></b> (0.6504)	<b>1.3483<sup>*</sup></b> (0.6776)
Log (Total Population)				-0.0506 (0.0373)
Proportion Female Population				0.6710 (3.3219)
Proportion Hispanic Population				-0.1068 (0.3669)
Proportion Foreign-born				<b>2.0006<sup>*</sup></b> (0.8277)
Constant	1.9428 <sup>***</sup> (0.0575)	1.6169 <sup>***</sup> (0.1486)	1.6140 <sup>***</sup> (0.1470)	1.7718 (1.6548)
Observations	301	301	301	301
R <sup>2</sup>	0.0455	0.0394	0.0641	0.0934
Akaike Inf. Crit.	483.4067	485.3504	479.5134	477.9233
<i>Note:</i>			*p<0.05; **p<0.01; ***p<0.001	

**Table 2.9. Unfreedom and the Black LBW Rate**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Racial Clustering	<b>0.0118</b> <sup>***</sup> (0.0033)			0.0055 (0.0035)	0.0050 (0.0035)	0.0069 (0.0037)	0.0060 (0.0034)
Black Gender Ratio 15-34		<b>0.0183</b> <sup>***</sup> (0.0033)		<b>0.0160</b> <sup>***</sup> (0.0036)	<b>0.0150</b> <sup>***</sup> (0.0036)	<b>0.0112</b> <sup>*</sup> (0.0043)	<b>0.0154</b> <sup>***</sup> (0.0040)
Black-White Jail Ratio			<b>-0.0005</b> <sup>**</sup> (0.0002)		-0.0003 (0.0002)	<b>-0.0003</b> <sup>*</sup> (0.0002)	-0.0002 (0.0001)
Log (Total Population)						-0.0011 (0.0008)	-0.0009 (0.0007)
Proportion Female Population						<b>0.2017</b> <sup>*</sup> (0.0801)	0.0550 (0.0757)
Proportion Hispanic Population						<b>0.0282</b> <sup>***</sup> (0.0072)	<b>0.0176</b> <sup>**</sup> (0.0067)
Proportion Foreign-born						<b>-0.082</b> <sup>***</sup> (0.0165)	<b>-0.0414</b> <sup>*</sup> (0.0160)
White LBW Rate							<b>0.8264</b> <sup>***</sup> (0.1084)
Constant	0.0340 <sup>***</sup> (0.0040)	0.0309 <sup>***</sup> (0.0032)	0.0510 <sup>***</sup> (0.0012)	0.0265 <sup>***</sup> (0.0042)	0.0298 <sup>***</sup> (0.0046)	-0.0540 (0.0381)	-0.0070 (0.0354)
Observations	301	301	301	301	301	301	301
R <sup>2</sup>	0.0407	0.0931	0.0268	0.0539	0.1105	0.2565	0.3800
Akaike Inf. Crit.	-1,817.3	-1,834.3	-1,813.0	-1,834.7	-1,836.1	-1,882.0	-1,934.7

*Note:*

\* p&lt;0.05; \*\* p&lt;0.01; \*\*\* p&lt;0.001

**Table 2.10. Unfreedom and the Black-White LBW Ratio**

	(1)	(2)	(3)	(4)	(5)	(6)
Racial Clustering	0.2850 (0.1535)			0.0422 (0.1644)	0.0456 (0.1651)	0.2509 (0.1897)
Black Gender Ratio 15-34		<b>0.6373***</b> (0.1548)		<b>0.6197***</b> (0.1694)	<b>0.6271***</b> (0.1717)	<b>0.8026***</b> (0.2207)
Black-White Jail Ratio			-0.0040 (0.0076)		0.0021 (0.0076)	0.0016 (0.0077)
Log (Total Population)						-0.0632 (0.0400)
Proportion Female Population						-4.3299 (4.0795)
Proportion Hispanic Population						0.0317 (0.3655)
Proportion Foreign- born						1.4363 (0.8393)
Constant	1.7847*** (0.1863)	1.5279*** (0.1484)	2.1506*** (0.0564)	1.4939*** (0.1992)	1.4698*** (0.2170)	3.9540* (1.9426)
Observations	301	301	301	301	301	301
R <sup>2</sup>	0.0114	0.0537	0.0010	0.0539	0.0541	0.0803
Akaike Inf. Crit.	493.9885	480.8343	497.1508	482.7677	484.6873	484.2449

Note:

\* p<0.05; \*\* p<0.01; \*\*\* p<0.001

**Table 2.11. Racism as a Fundamental Cause of the Black LBW Rate**

	(1)	(2)	(3)	(4)
Black-White Occupational Prestige Gap	0.0079 (0.0057)	0.0098 (0.0058)	<b>0.0116*</b> (0.0057)	<b>0.0133**</b> (0.0051)
Black-White HH Income Gap	-0.0129 (0.0076)	-0.0120 (0.0079)	-0.0112 (0.0075)	-0.0035 (0.0068)
Black-White BA Gap	-0.0075 (0.0045)	-0.0078 (0.0047)	<b>-0.0089*</b> (0.0044)	<b>-0.0160***</b> (0.0041)
Black-White Unemployment Gap	0.0017 (0.0013)	0.0014 (0.0013)	0.0010 (0.0012)	0.0019 (0.0011)
Black-White Poverty Gap	<b>-0.0027*</b> (0.0014)	-0.0015 (0.0015)	-0.0020 (0.0014)	-0.0002 (0.0013)
Racial Isolation	<b>0.0236***</b> (0.0039)	<b>0.0322***</b> (0.0059)	<b>0.0266***</b> (0.0057)	<b>0.0214***</b> (0.0052)
Poverty Isolation	<b>0.0393**</b> (0.0144)	<b>0.0380**</b> (0.0144)	0.0275 (0.0140)	<b>0.0289*</b> (0.0126)
Black Gender Ratio 15-34		0.0017 (0.0041)	0.0015 (0.0048)	0.0084 (0.0044)
Racial Clustering		<b>-0.0125**</b> (0.0044)	-0.0081 (0.0045)	<b>-0.0085*</b> (0.0040)
Black-White Jail Ratio		-0.0001 (0.0002)	-0.0001 (0.0002)	-0.0001 (0.0001)
Log (Total Population)			-0.0005 (0.0007)	-0.0004 (0.0007)
Proportion Female Population			<b>0.1672*</b> (0.0758)	0.0106 (0.0707)
Proportion Hispanic Population			<b>0.0233**</b>	<b>0.0175*</b>

			(0.0075)	(0.0068)
Proportion Foreign-born			<b>-0.0723</b> ***	<b>-0.0316</b> *
			(0.0156)	(0.0149)
White LBW Rate				<b>0.8775</b> ***
				(0.1061)
Constant	0.0422***	0.0500***	-0.0253	0.0165
	(0.0089)	(0.0106)	(0.0369)	(0.0335)
<hr/>				
Observations	301	301	301	301
R <sup>2</sup>	0.2564	0.2782	0.3713	0.4931
Akaike Inf. Crit.	-1,882.0490	-1,885.0080	-1,918.6090	-1,981.3960
<hr/>				
<i>Note:</i>	* p<0.05; ** p<0.01; *** p<0.001			

**Table 2.12. Racism as a Fundamental Cause of the Black-White LBW Ratio**

	(1)	(2)	(3)
Black-White Occupational Prestige Gap	<b>0.9491<sup>***</sup></b> (0.2761)	<b>1.1144<sup>***</sup></b> (0.2805)	<b>0.9352<sup>**</sup></b> (0.2864)
Black-White HH Income Gap	-0.2409 (0.3691)	0.0235 (0.3821)	-0.0685 (0.3770)
Black-White BA Gap	<b>-1.0709<sup>***</sup></b> (0.2199)	<b>-1.2038<sup>***</sup></b> (0.2255)	<b>-1.1847<sup>***</sup></b> (0.2236)
Black-White Unemployment Gap	<b>0.2167<sup>***</sup></b> (0.0609)	<b>0.1746<sup>**</sup></b> (0.0629)	<b>0.1687<sup>**</sup></b> (0.0620)
Black-White Poverty Gap	-0.0934 (0.0661)	-0.0264 (0.0705)	0.0233 (0.0710)
Racial Isolation	0.2844 (0.1895)	0.2713 (0.2880)	0.5009 (0.2886)
Poverty Isolation	<b>1.4437<sup>*</sup></b> (0.6959)	1.3110 (0.6977)	1.1050 (0.7066)
Black Gender Ratio 15-34		<b>0.4944<sup>*</sup></b> (0.2009)	<b>0.6249<sup>*</sup></b> (0.2450)
Racial Clustering		-0.2889 (0.2148)	-0.2729 (0.2264)
Black-White Jail Ratio		-0.0005 (0.0077)	-0.0033 (0.0078)
Log (Total Population)			-0.0424 (0.0378)
Percent Female Population			-6.1862 (3.8284)
Percent Hispanic Population			0.2699 (0.3794)
Percent Foreign-born			<b>1.5718<sup>*</sup></b> (0.7880)
Constant	1.5984 <sup>***</sup> (0.4313)	1.2471 <sup>*</sup> (0.5128)	4.6958 <sup>*</sup> (1.8619)

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Observations	301	301	301
R <sup>2</sup>	0.1713	0.1927	0.2353
Akaike Inf. Crit.	452.8705	451.0210	442.7066

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*Note:*

\*p<0.05; \*\*p<0.01; \*\*\*p<0.001

**Table 2.13. Exploratory Factor Analysis Regression Models**

	Black LBW Rate			Black-White LBW Gap		
	(1)	(2)	(3)	(4)	(5)	(6)
Power and Prestige	<b>-0.0018*</b> (0.0007)	<b>-0.0017*</b> (0.0007)	<b>-0.0027***</b> (0.0007)	<b>-0.0874**</b> (0.0329)	<b>-0.0854**</b> (0.0323)	<b>-0.1779***</b> (0.0381)
Spatial Disadvantage		<b>0.0051***</b> (0.0006)	<b>0.0046***</b> (0.0006)		<b>0.1042***</b> (0.0309)	<b>0.1674***</b> (0.0360)
Log (Total Population)			<b>-0.0015*</b> (0.0006)			<b>-0.0863*</b> (0.0363)
Percent Female Population			0.1062 (0.0586)			-0.1616 (3.2618)
Percent Hispanic Population			<b>0.0248***</b> (0.0066)			0.5602 (0.3724)
Percent Foreign-born			-0.0259 (0.0152)			<b>2.1558**</b> (0.8125)
White LBW Rate			<b>0.7980***</b> (0.1038)			
Constant	0.0481*** (0.0007)	0.0481*** (0.0006)	-0.0061 (0.0294)	2.1257*** (0.0313)	2.1257*** (0.0308)	3.0759 (1.6631)
Observations	301	301	301	301	301	301
R <sup>2</sup>	0.0199	0.1986	0.4375	0.0231	0.0589	0.1290
Akaike Inf. Crit.	-1,810.95	-1,869.54	-1,966.08	490.4055	481.1569	465.8756

*Note:*

\*p&lt;0.05; \*\*p&lt;0.01; \*\*\*p&lt;0.001

## APPENDIX 2.A

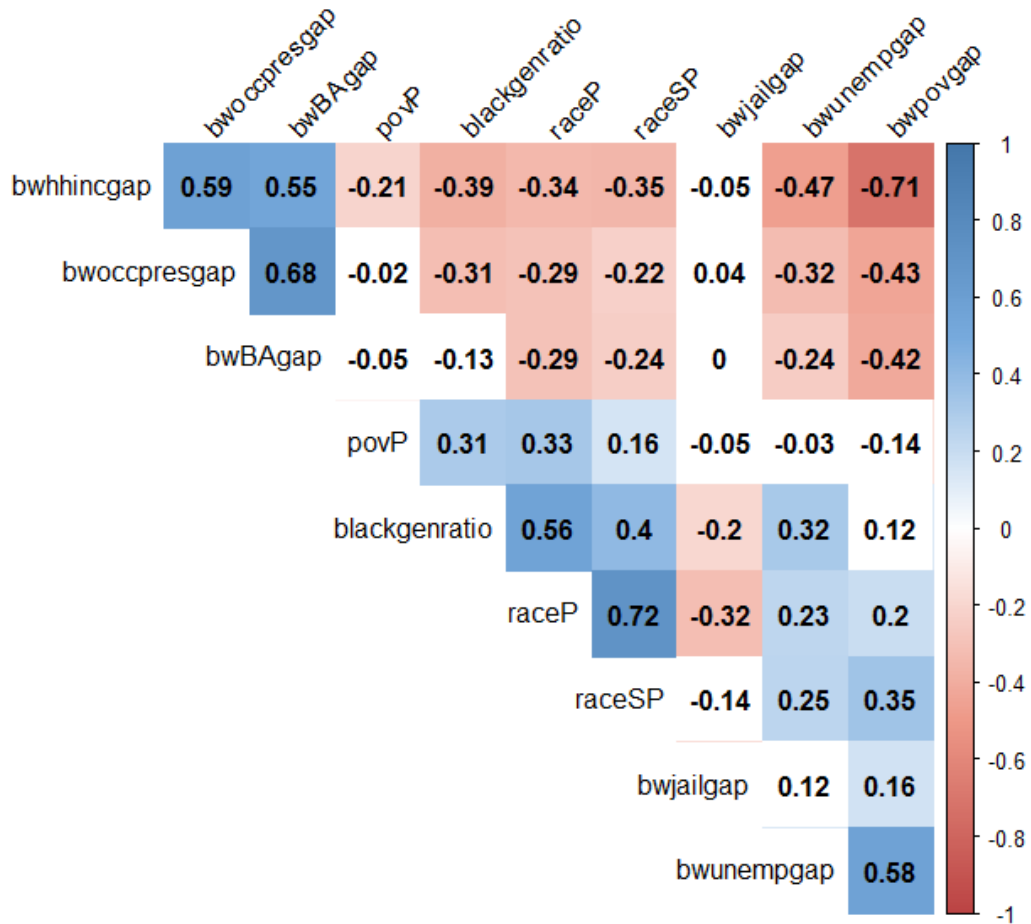


Figure 2.2. Correlation matrix for key independent variables. Blue shades indicate a positive correlation and red shades indicate a negative correlation. Darker shades indicate a stronger correlation. Boxes are white if the correlation coefficient is not statistically significant at the  $\alpha = 0.01$  level. Correlation coefficients are shown inside boxes.

**Table 2.14. Power and Prestige Mechanisms with Sociodemographic Controls**

	Black LBW Rate					Black-White LBW Ratio				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Occupational Prestige	-0.0061 (0.0043)					-0.4002 (0.2345)				
HH Income		<b>-0.0158***</b> (0.0047)					<b>-1.0269***</b> (0.2522)			
BA Attainment			<b>-0.0141***</b> (0.0033)					<b>-0.9280***</b> (0.1743)		
Unemployment				<b>0.0023*</b> (0.0010)					<b>0.2146***</b> (0.0548)	
Poverty					0.0005 (0.0009)					<b>0.1180*</b> (0.0486)
Log (Total Population)	0.0001 (0.0007)	-0.0002 (0.0007)	0.00003 (0.0006)	0.00004 (0.0007)	0.00005 (0.0007)	-0.0220 (0.0361)	-0.0403 (0.0356)	-0.0257 (0.0346)	-0.0279 (0.0354)	-0.0369 (0.0367)
Percent Female Population	<b>0.2524***</b> (0.0604)	<b>0.2270***</b> (0.0599)	<b>0.2359***</b> (0.0586)	<b>0.2321***</b> (0.0612)	<b>0.2624***</b> (0.0601)	5.5716 (3.2163)	4.1501 (3.1665)	5.0929 (3.0780)	3.8473 (3.1886)	<b>6.3524*</b> (3.1860)
Percent Hispanic Population	<b>0.0163*</b> (0.0072)	<b>0.0189**</b> (0.0069)	<b>0.0201**</b> (0.0068)	<b>0.0142*</b> (0.0068)	<b>0.0141*</b> (0.0071)	0.0954 (0.3892)	0.2861 (0.3718)	0.4113 (0.3653)	0.0384 (0.3607)	0.1551 (0.3825)
Percent Foreign-born	<b>-0.0418*</b> (0.0164)	<b>-0.0362*</b> (0.0162)	<b>-0.0392*</b> (0.0159)	<b>-0.0385*</b> (0.0164)	<b>-0.0412*</b> (0.0167)	1.4615 (0.8433)	<b>1.7330*</b> (0.8273)	1.3797 (0.8096)	1.6041 (0.8270)	<b>1.6722*</b> (0.8437)
White LBW Rate	<b>0.8189***</b> (0.1118)	<b>0.8483***</b> (0.1100)	<b>0.8956***</b> (0.1102)	<b>0.8548***</b> (0.1133)	<b>0.8131***</b> (0.1149)					
Constant	-0.0943** (0.0297)	-0.0741* (0.0298)	-0.0837** (0.0285)	-0.0935** (0.0291)	-0.1043*** (0.0290)	-0.2652 (1.6089)	0.9841 (1.6019)	0.2704 (1.5239)	-0.0544 (1.5538)	-1.0636 (1.5672)
Observations	301	301	301	301	301	301	301	301	301	301
R <sup>2</sup>	0.3290	0.3496	0.3640	0.3354	0.3252	0.3523	0.0776	0.1111	0.0740	0.0448
Akaike Inf. Crit.	-1,914.9890	-1,924.3890	-1,931.1130	-1,917.8830	-1,913.2670	494.6420	481.1360	469.9776	482.3254	491.6458

Note:

\*p&lt;0.05; \*\*p&lt;0.01; \*\*\*p&lt;0.001

**Table 2.15. Beneficial Social Connections Mechanisms with Sociodemographic Controls and Interaction Terms**

	Black LBW Rate				Black-White LBW Ratio			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Racial Isolation	<b>0.0261</b> <sup>***</sup> (0.0037)		0.0297 (0.0185)	<b>0.0382</b> <sup>*</sup> (0.0163)	<b>0.8954</b> <sup>***</sup> (0.2122)		1.6239 (0.9344)	1.5357 (0.9494)
Poverty Isolation		<b>0.0591</b> <sup>***</sup> (0.0114)	<b>0.0547</b> <sup>**</sup> (0.0205)	<b>0.0501</b> <sup>**</sup> (0.0182)		<b>2.1445</b> <sup>***</sup> (0.6411)	<b>2.5511</b> <sup>*</sup> (1.0361)	2.0602 (1.0606)
Log (Total Population)	-0.0012 (0.0006)	0.0004 (0.0006)		-0.0009 (0.0006)	-0.0645 (0.0368)	-0.0096 (0.0356)		-0.0534 (0.0375)
Percent Female Population	<b>0.1316</b> <sup>*</sup> (0.0586)	<b>0.1987</b> <sup>***</sup> (0.0588)		<b>0.1170</b> <sup>*</sup> (0.0581)	1.3619 (3.3202)	3.6303 (3.2432)		0.7758 (3.3254)
Percent Hispanic Population	<b>0.0192</b> <sup>**</sup> (0.0064)	0.0078 (0.0066)		<b>0.0149</b> <sup>*</sup> (0.0064)	0.0560 (0.3594)	-0.3370 (0.3655)		-0.1192 (0.3673)
Percent Foreign-born	<b>-0.0311</b> <sup>*</sup> (0.0153)	<b>-0.0388</b> <sup>*</sup> (0.0157)		<b>-0.0313</b> <sup>*</sup> (0.0151)	<b>1.9615</b> <sup>*</sup> (0.8316)	<b>1.6666</b> <sup>*</sup> (0.8341)		<b>1.9746</b> <sup>*</sup> (0.8285)
White LBW Rate	<b>0.7410</b> <sup>***</sup> (0.1030)	<b>0.7652</b> <sup>***</sup> (0.1065)		<b>0.7265</b> <sup>***</sup> (0.1017)				
Racial Isolation x Poverty Isolation			-0.0171 (0.0722)	-0.0656 (0.0635)			-4.4002 (3.6517)	-3.2253 (3.6957)
Constant	-0.0270 (0.0289)	-0.0868 <sup>**</sup> (0.0280)	0.0283 <sup>***</sup> (0.0048)	-0.0332 (0.0288)	1.8543 (1.6626)	-0.1893 (1.5635)	1.3788 <sup>***</sup> (0.2443)	1.5875 (1.6689)
Observations	301	301	301	301	301	301	301	301
R <sup>2</sup>	0.4227	0.3809	0.2357	0.4425	0.0812	0.0613	0.0686	0.0958
Akaike Inf. Crit.	-1,960.257	-1,939.241	-1,881.783	-1,966.779	479.9495	486.3915	480.0455	479.1419

Note:

\* p&lt;0.05; \*\* p&lt;0.01; \*\*\* p&lt;0.001

**Table 2.16. (Un)Freedom Mechanisms with Sociodemographic Controls**

	Black LBW Rate			Black-White LBW Ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
Racial Clustering	<b>0.0087*</b> (0.0034)			0.3680 (0.1902)		
Black Gender Ratio 15-34		<b>0.0177***</b> (0.0039)			<b>0.8425***</b> (0.2131)	
Black-White Jail Ratio			<b>-0.0003*</b> (0.0001)			-0.0052 (0.0077)
Log (Total Population)	-0.0007 (0.0007)	-0.0003 (0.0006)	0.0001 (0.0007)	-0.0550 (0.0407)	-0.0395 (0.0357)	-0.0192 (0.0362)
Percent Female Population	<b>0.2330***</b> (0.0606)	0.0457 (0.0750)	<b>0.2671***</b> (0.0596)	4.8092 (3.2666)	-3.9095 (4.0316)	6.1280 (3.2138)
Percent Hispanic Population	<b>0.0157*</b> (0.0068)	<b>0.0146*</b> (0.0066)	<b>0.0155*</b> (0.0069)	-0.0245 (0.3692)	-0.0261 (0.3589)	-0.0969 (0.3709)
Percent Foreign-born	<b>-0.0373*</b> (0.0164)	<b>-0.0445**</b> (0.0159)	<b>-0.0447**</b> (0.0163)	<b>1.7088*</b> (0.8521)	1.2529 (0.8274)	1.4499 (0.8468)
White LBW Rate	<b>0.7908***</b> (0.1099)	<b>0.8512***</b> (0.1080)	<b>0.7718***</b> (0.1107)			
Constant	-0.0883** (0.0293)	-0.0058 (0.0352)	-0.1026*** (0.0288)	-0.1829 (1.6073)	3.7290 (1.9262)	-0.8117 (1.5799)
Observations	301	301	301	301	301	301
R <sup>2</sup>	0.3389	0.3695	0.3359	0.0379	0.0747	0.0272
Akaike Inf. Crit.	-1,919.4680	-1,933.7350	-1,918.0820	493.8016	482.0562	497.1403

Note:

\*p<0.05; \*\*p<0.01; \*\*\*p<0.001

## Chapter 3. Routes to Low Birth Weight (or Not): Characteristics of Exceptional Communities

### 3.1 Introduction

The preceding chapters have described, in detail, the robust gap in LBW between babies born to black and white mothers in the US. While these disparities are striking, aggregate rates of LBW hide variation across geographies in the US. Place is a robust determinant of health, implying that “your zip code [may matter] more than your genetic code” (Graham 2016). Table 3.1, which shows the black-white LBW ratio for ten MSAs, suggests that this may also be the case for black-white inequalities in LBW. The first five rows of Table 3.1 show the five MSAs with the lowest rate of black LBW relative to the white LBW rate. For example, in Kennewick-Richland, Washington, white mothers are actually more likely to give birth to LBW infants than black mothers. In this community, for every three black infants that are born LBW, there are four white infants born LBW. In contrast, the last five rows of Table 3.1 show the five MSAs with the highest rate of black LBW relative to the white LBW rate. For example, in Ithaca, New York, there are almost six black infants that are born LBW for every 1 white infant born LBW. These differences across MSAs suggest that place-specific social conditions are likely playing a significant role in the black-white gap in LBW.

A primary way in which place matters for health is through structural inequalities between racial and ethnic groups. Using fundamental causality as a theoretical framework, the analyses presented in Chapter 2 suggest that racial inequalities in prestige, power, beneficial social connections, and freedom, which are measured as racial differences in socioeconomic status, residential mobility, and contact with the criminal legal system, explain a substantial amount of the variation in both the black LBW rate and the black-white LBW ratio across MSAs. However, these key predictors and relevant covariates by no means explain all of the

variation in racial differences in LBW across MSAs. There are two possible sources of this unexplained variance. First, the remaining variance cannot be explained and is instead due to random chance. The second explanation is that relevant characteristics of MSAs have been excluded, producing omitted variable bias. The analysis presented here explore this second source of unexplained variance and draws on methods from Caldwell (1986) and Kuhn (2010) to identify MSAs that stand out as “exceptional” in regards to the outcomes. MSAs are considered exceptional if they have significantly higher or lower observations of the outcomes than expected given the predictive models used in Chapter 2.

Identifying and describing these communities is a necessary first step in understanding how social conditions of certain areas produce inequalities in health. Indeed, analyses by Caldwell (1986) identified low-income countries with higher and lower rates of mortality that would be expected given their economic standing. From this analysis, Caldwell (1986) concludes that while investments in health systems certainly matter, the primary determinant of exceptional mortality is women’s access to education which also influences the intermediary mechanism of women’s ability to control their fertility. Kuhn (2010) revisits this analysis twenty-five years later, noting early on that Caldwell’s (1986) original discussion never elaborated on what conditions produce social consensus towards the value of educational and health goals that is thought to be the linchpin of low mortality despite poor economic conditions. In their analysis, Kuhn (2010) suggests that there is no “one-size-fits-all” route to low mortality. Rather, countries should seek to surpass a floor level of success on a few measures of development, such as schooling, health systems, and poverty, and a few measures of governance, such as democracy, efficacy, and corruption. That is, if low-income countries seek to improve mortality, they should aim investment efforts at increasing schooling and decreasing corruption, for example, but it

would be inefficient to concentrate improvement efforts on all indicators. While these analyses by Caldwell (1986) and Kuhn (2010) are informative, they still do not fully explain what social conditions produce routes to low and high mortality.

The analysis presented here applies the logic from these studies and extends the methodology by identifying exceptional MSAs not by differences in relative rank (e.g., Eritrea is a superior achiever because its mortality rate rank is 30 places above its gross domestic product rank) but through post-estimation using a regression model informed by theories of racism and health. I take this approach based on the assumption that once structural inequalities are controlled for, MSAs that stand out as exceptional in regards to LBW have certain social conditions not captured by these structural measures of racism that influence racial disparities in LBW. This approach is also beneficial as it aims to identify communities that have lower rates of the outcomes than expected, a category that is often overlooked in public health and medical sociology. Identifying these communities will also allow for rich description of the social climate in these areas using a novel data source, Twitter, which will be the focus of Chapter 4.

### 3.2. Data and Methods

The theoretical orientation, data sources, and regression analysis have already been described in detail in Chapter 2. Briefly, this analysis builds upon the regression results from Chapter 2 and is informed by fundamental cause theory (FCT). In naming racism as a fundamental cause of racial health inequalities, Phelan and Link (2015) identify prestige, power, beneficial social connections, and freedom as race-specific flexible resources that maintain the relationship between racism as a fundamental cause and health outcomes. Using data from various sources, I estimate the association between MSA-level measures of each mechanism, as well as relevant population characteristics and the black LBW rate as well as the black-white

ratio in LBW. As noted above, I find that MSA-level measures of the FCT mechanisms account for a considerable amount of the variation but do not appear to capture all the ways in which social conditions within MSAs matter for infant health. To identify exceptional MSAs, I calculate the standardized residuals from the fully adjusted models for both outcomes and select the MSAs with standardized residuals 2 standard deviations above or below the conditional mean for each outcome. Below, I provide a descriptive overview of each exceptional MSA, with a specific focus on those MSAs that have higher or lower black LBW rates as well as smaller or larger black-white LBW ratios than we would expect based on the model specification.

### 3.3 Results: Description of Exceptional Communities

Table 3.2 shows the MSAs with lower black LBW rates and higher black LBW rates than expected given the independent variables and covariates in the models. I find that five MSAs have lower rates of LBW among babies born to black mothers than expected and eight MSAs have higher rates of the outcome than expected. Table 3.2 also shows the number of black births in each MSA, as well as the observed black LBW rate and the predicted value of the outcome. Based on the results in Table 3.2, it is clear that many MSAs that stand out as exceptional have relatively small black populations and relatively few births to black mothers between 2013 and 2016. The exception to this is Alexandria, Louisiana where almost 30 percent of the population identifies as black or African American and 2387 births to black mothers occurred over the four years included in this analysis. For the remaining exceptional MSAs, however, black people are underrepresented in the population. An extreme case of this is the Kennewick-Richland, Washington MSA where less than 2 percent of the population identified as black or African American.

Even still, the gaps between the expected and observed rates of black LBW in these MSAs is quite large. For example, in Kokomo, Indiana only 2.5 percent of all births to black mothers are LBW while the sociodemographic conditions in Kokomo would predict a black LBW rate over twice that. Likewise, in Ithaca, New York the observed rate of LBW is nearly 7 percent. While this rate is well below the national average for LBW among babies born to black mothers, it is well above the expected rate of black LBW (3.93 percent).

Table 3.3 shows the MSAs with lower black-white LBW ratios and higher black-white LBW ratios than expected given the model specification. Table 3.3 also shows the number of black and white births in each MSA as well as the observed and predicted black-white LBW ratios. As was the case with the exceptional MSAs shown in Table 3.2, many of the MSAs with lower or higher black-white LBW ratios than expected have relatively fewer black births than white births across the four years included in this analysis. The singular exception to this appears to be Vineland-Bridgeton, New Jersey where 1972 babies were born to black mothers and 1327 babies were born to white mothers between 2013 and 2016. In this same community, the social and demographic characteristics included in model specifications would imply a black-white LBW ratio of 2.53. That is, we would expect that for every 2 white infants born LBW, 5 black infants would be LBW as well. However, natality data from this community shows that the true black-white LBW ratio is 1.46: for every 2 white infants born LBW, 3 black infants are born LBW.

In comparison, the San Luis Obispo-Paso Robles-Arroyo Grande, California MSA registered 118 births to mothers who identified as black but 5647 births to mothers who identified as white. That is, for every infant born to a black mother in the MSA, approximately 48 infants were born to white mothers. For this MSA, infants born to black mothers are at a

greater risk of LBW than we would expect. While the model specification predicts a black-white LBW ratio of 2.21, already slightly above the national black-white LBW ratio, natality data from this community shows that the actual black-white LBW ratio is 3.63. However, this is not the most drastic difference between the expected and observed inequality in LBW. In Ithaca, New York MSA, the expected black-white LBW ratio is 2.54 while the observed rate is a staggering 5.66. That is, for every white infant born LBW in Ithaca, nearly 6 black infants are born LBW. It is also worth noting that Ithaca, as well as 5 other MSAs, have both higher or lower black LBW rates as well as smaller or larger black-white LBW ratios than we would expect based on the model specification. Descriptive statistics for these 6 MSAs are shown in Table 3.4.

As Table 3.4 shows, four MSAs have lower rates of LBW among babies born to black mothers and smaller black-white gaps in LBW than the predictors in the models would expect. In addition, two MSAs have higher black LBW rates and wider black-white LBW ratios than expected. Looking at the demographic characteristics of these MSAs, shown in the last five rows of Table 3.4, it is clear that all exceptional MSAs have smaller populations than the average MSA in the United States. While MSAs in the United States are skewed because of large metropolitan areas such as New York City, Los Angeles, and Chicago, the MSAs that are exceptional in terms of the LBW outcomes analyzed here have population sizes smaller than the median as well (312,676). In fact, Kokomo, Indiana and Ocean City, New Jersey have populations that are only slightly larger than the minimum population size of an MSA in the full sample of 301 MSAs (80,368). Still, it would be incorrect to call any of these MSAs “small” in an absolute sense as they are, by definition, sizeable metropolitan areas.

However, as noted in Table 3.2, the MSAs identified in Table 3.4 do have much smaller African American populations than MSAs in the US more broadly. At present, African

Americans constitute roughly 13 percent of the US population. In the 301 MSAs in my full sample, African Americans also constitute 13 percent of the population on average. For the 6 MSAs that are identified as exceptional for both outcomes, African Americans are consistently underrepresented. As was the case for population size overall, the proportion of African American residents in the exceptional MSAs tends to fall between the 1<sup>st</sup> quartile (0.05) and the median (0.09) of the larger sample of 301 MSAs. While the MSAs shown in Table 3.4 all have small African American populations, they are much more varied in regards to the proportion of residents that are Hispanic and those that are foreign-born. For example, although the Kennewick-Richland MSA has a small African American population, Hispanic and foreign-born residents are over-represented in this community. In contrast, black, Hispanic, and foreign-born residents are all underrepresented in the Morgantown, WV MSA.

In regards to the key predictor variables in the models, each of which indeed do capture some aspect of black-white inequalities in power, prestige, beneficial social connections, and unfreedom, a qualitative appraisal of these characteristics suggests that on the whole, these MSAs do not appear dramatically different from the larger sample of 301 MSAs. That is, the MSAs that have lower rates of black LBW and smaller black-white gaps in LBW than expected do not seem to be places in which black residents are more socially and economically disadvantaged than black residents in other MSAs. For example, in the Kingston, NY MSA, the black-white unemployment gap is smaller than the black-white unemployment gap across all 301 MSAs included in the analysis. Likewise, the degree of racial clustering in these communities is below the degree of clustering for all MSAs. In fact, in all but one of the “better than expected” MSAs, there is no racial clustering among black residents. While measures of clustering are

influenced by the size of the black population, the degree of racial isolation is also well below the average for all MSAs.

However, the descriptive statistics shown in Table 3.4 also suggest that in some regards, these communities have greater social and economic inequalities between black and white residents than the larger sample of 301 MSAs. In Kokomo, IN the black-white gap in BA attainment is such that for every black resident with a bachelor's degree, there are three white residents with the same level of educational attainment. In this same MSA, the black-white employment gap is such that for every white resident experiencing unemployment, three black residents are also unemployed. In Kennewick-Richland, young black women outnumber young black men such that for every five young black women in the MSA, there are four young black men. This is particularly striking considering that at the aggregate, men slightly outnumber women in Kennewick-Richland overall. In Kingston, we see the same level of inequality in BA attainment as in Kokomo as well as greater inequality occupational attainment and household income, although the disparities are not as striking. However, Kingston does have a dramatic skew in the black jail population relative to the white jail population such that for every two white people in jail in Kingston there are 17 black people also in jail. In Morgantown, the degree of poverty isolation is slightly above the average for all MSAs but in regards to black-white inequalities in segregation and economic standing, conditions in Morgantown seem to imply a higher level of racial equality than is the case for most MSAs. The one way in which Morgantown truly stands out is the black gender ratio, which is skewed towards young black men. In Morgantown, for every ten black men between the ages of 15 and 34, there are only four black women.

Turning to the two MSAs that have both higher black LBW rates and large black-white gaps in LBW than we would expect given the characteristics shown in Table 3.4, it also appears that Ocean City, New Jersey and Ithaca, New York are not strikingly different from all MSAs included in this analysis. In Ocean City, there is a greater inequality in occupational attainment between black and white residents but less inequality in regards to the median household income of black and white households. Likewise, while the black-white gap in BA attainment in Ocean City is more imbalanced than in all 301 MSAs, there is less inequality in unemployment and poverty. Ithaca shows similar contradictions. In Ithaca, the black-white gaps in occupational and educational attainment are less pronounced. However, the inequalities in household income, unemployment, and poverty are greater in Ithaca than in all MSAs. In addition, while the degree of racial isolation and clustering is relatively low, the degree of poverty isolation is relatively higher. Ithaca does, however, stand out in regards to the remaining measures of unfreedom as the black gender ratio is just above 1.00 and the jail population in Ithaca is comprised of more white people than black people.

### 3.4 Discussion and Conclusion

The goal of this analysis is to identify those metropolitan areas in the US that stand out as “exceptional” in regards to the black LBW rate and/or the black-white LBW ratio once theoretically informed measures of structural racism and population characteristics have been accounted for. This approach has been used in previous analysis by Caldwell (1986) and Kuhn (2010) to identify countries with higher and lower rates of mortality, both among infants and in the population overall, that would be expected given the economic conditions of these countries (e.g., income per head, gross domestic product). While both authors identify likely mechanisms among countries identified as “achievers” (i.e., low-income countries with exceptionally low

mortality) such as women's education, aspects of governance, and more robust health systems, both analyses conclude that there is no "one-size-fits-all" route to low mortality.

This conclusion appears to be true for rates of LBW across MSAs as well. Overall, the MSAs shown in Table 3.4, and to some extent the 19 MSAs identified as exceptional overall, are not unequivocally "good" or "bad" in regards to social, economic, and residential inequalities between black and white residents. While some exceptional MSAs show drastic differences from the overall sample in regards to social and economic inequalities, they are by no means places that "tick all boxes". Instead, these MSAs with higher or lower rates of black LBW and larger or smaller black-white LBW gaps seem, perhaps surprisingly, relatively unexceptional. This finding implies that there may be characteristics of these communities not shown here that can help explain why they under- or over-perform in regards to the outcomes.

One possibility is that there are social conditions within these MSAs that increase the likelihood of exposure to racial discrimination but are not captured by the measures of racial inequality included in the regression analysis. Research on the association between experiences of racial discrimination and health status suggests that racial discrimination operates as a form of psychosocial stress. Given that stress is an established risk factor for LBW, greater exposure to racial discrimination is likely to increase the risk of LBW. Individual-level analyses support this notion, but these analyses rely on self-reports of discrimination which may be subject to recall biases and may underestimate the daily slights and microaggressions that racial minorities experience in their communities. As such, researchers have begun to investigate the utility of novel data sources such as Twitter, Google Trends, and digital trace data to proxy racialized social climates. In the next empirical chapter, I use historical, geocoded data from Twitter to

determine if the 19 exceptional communities identified here produce digital traces about African Americans with a distinctly positive or negative sentiment.

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**Table 3.1. The Black-White Gap in LBW for Select MSAs**

Metropolitan Statistical Area	Black-White LBW Ratio
Kennewick-Richland, WA	0.74
Beckley, WV	0.87
Kingston, IN	0.93
Kokomo, IN	0.96
Morgantown, WV	1.01
San Luis Obispo-Paso Robles- Arroyo Grande, CA	3.63
College Station-Bryan, TX	3.72
Kankakee, IL	4.00
Ocean City, NJ	4.58
Ithaca, NY	5.66

**Table 3.2. MSAs with Exceptional Black LBW Rate**

	Percent Black Population	Number of Black Births	Black LBW Rate	Predicted Value	Model Residuals	Standardized Residuals
<b>BETTER THAN EXPECTED</b>						
<i>Kokomo, IN</i>	<i>7.09</i>	<i>365</i>	<i>0.0247</i>	<i>0.0581</i>	<i>-0.0335</i>	<i>-3.9455</i>
<i>Kennewick-Richland, WA</i>	<i>1.67</i>	<i>244</i>	<i>0.0123</i>	<i>0.0395</i>	<i>-0.0272</i>	<i>-3.2580</i>
<i>Beckley, WV</i>	<i>7.14</i>	<i>232</i>	<i>0.0388</i>	<i>0.0609</i>	<i>-0.0221</i>	<i>-2.6591</i>
<i>Kingston, NY</i>	<i>5.86</i>	<i>143</i>	<i>0.0280</i>	<i>0.0484</i>	<i>-0.0204</i>	<i>-2.3908</i>
<i>Morgantown, WV</i>	<i>3.69</i>	<i>198</i>	<i>0.0404</i>	<i>0.0585</i>	<i>-0.0181</i>	<i>-2.1945</i>
<b>WORSE THAN EXPECTED</b>						
Fort Smith, AR-OK	3.84	524	0.0649	0.0476	0.0173	2.0057
Owensboro, KY	3.94	243	0.0617	0.0445	0.0172	2.0648
Alexandria, LA	29.47	2387	0.0792	0.0610	0.0182	2.1171
<i>Ocean City, NJ</i>	<i>4.73</i>	<i>131</i>	<i>0.0611</i>	<i>0.0401</i>	<i>0.0210</i>	<i>2.4847</i>
Wheeling, WV-OH	3.27	162	0.0741	0.0505	0.0235	2.8437
<i>Ithaca, NY</i>	<i>4.15</i>	<i>120</i>	<i>0.0667</i>	<i>0.0393</i>	<i>0.0274</i>	<i>3.2820</i>
Sierra Vista-Douglas, AZ	3.87	186	0.0806	0.0498	0.0308	4.0808
Johnstown, PA	3.41	275	0.0873	0.0527	0.0345	4.1407

*Note:* MSAs with standardized residuals 2 standard deviations above or below the mean for both outcomes are shown in italics.

**Table 3.3. MSAs with Exceptional Black-White LBW Ratio**

	Number of Black Births	Number of White Births	Black- White LBW Ratio	Predicted Value	Model Residuals	Standardized Residuals
<b>BETTER THAN EXPECTED</b>						
<i>Kokomo, IN</i>	<i>365</i>	<i>3894</i>	<i>0.9602</i>	<i>2.5255</i>	<i>-1.5653</i>	<i>-3.2846</i>
<i>Kennewick-Richland, WA</i>	<i>244</i>	<i>8047</i>	<i>0.7383</i>	<i>2.2786</i>	<i>-1.5403</i>	<i>-3.2833</i>
Vineland-Bridgeton, NJ	1327	1972	1.4604	2.5308	-1.0704	-2.2437
<i>Kingston, NY</i>	<i>143</i>	<i>893</i>	<i>0.9251</i>	<i>1.9819</i>	<i>-1.0567</i>	<i>-2.1904</i>
<i>Morgantown, WV</i>	<i>198</i>	<i>7651</i>	<i>1.0102</i>	<i>1.9568</i>	<i>-0.9466</i>	<i>-2.0088</i>
<b>WORSE THAN EXPECTED</b>						
Midland, TX	457	4131	3.3433	2.3862	0.9571	2.0789
Oxnard-Thousand Oaks- Ventura, CA	462	10674	2.8218	1.7678	1.0541	2.1999
Bloomington, IN	231	6495	2.9242	1.8823	1.0419	2.2527
Kankakee, IL	890	3435	3.9926	2.5533	1.4393	3.0097
San Luis Obispo-Paso Robles-Arroyo Grande, CA	118	5647	3.6346	2.2131	1.4215	3.1432
<i>Ocean City, NJ</i>	<i>131</i>	<i>974</i>	<i>4.5755</i>	<i>2.2180</i>	<i>2.3575</i>	<i>4.9289</i>
<i>Ithaca, NY</i>	<i>120</i>	<i>2631</i>	<i>5.6581</i>	<i>2.5384</i>	<i>3.1197</i>	<i>6.6295</i>

*Note:* MSAs with standardized residuals 2 standard deviations above or below the mean for both outcomes are shown in italics.

**Table 3.4. Population Characteristics of Selected Exceptional MSAs**

	<i>Better Than Expected</i>				<i>Worse Than Expected</i>		<b>All Exceptional MSAs</b>	<b>All MSAs</b>
	Kokomo, IN	Kennewick-Richland, WA	Kingston, NY	Morgantown, WV	Ocean City, NJ	Ithaca, NY		
Black-White Occupational Prestige Gap	0.84	0.70	0.66	0.99	0.63	0.85	0.82	0.71
Black-White Household Income Gap	0.47	0.78	0.58	0.58	0.67	0.46	0.66	0.60
Black-White BA Gap	0.36	0.70	0.36	0.59	0.29	0.62	0.56	0.60
Black-White Unemployment Gap	2.11	1.69	1.45	0.82	1.84	2.59	1.81	2.11
Black-White Poverty Gap	2.98	1.95	2.51	2.22	1.57	3.00	2.31	2.42
Racial Isolation	0.19	0.03	0.12	0.10	0.17	0.08	0.16	0.27
Poverty Isolation	0.24	0.23	0.15	0.26	0.16	0.30	0.23	0.23
Black Gender Ratio	1.04	1.24	0.69	0.40	0.91	1.01	0.74	0.94
Racial Clustering	1.00	1.01	1.17	1.00	1.00	1.01	1.08	1.20
Black-White Jail Gap	4.43	5.01	8.50	3.50	6.34	0.53	6.49	6.16
Total Population	82765	271373	181300	135477	95805	103855	193019	853874
Proportion Female	0.52	0.49	0.50	0.48	0.51	0.51	0.50	0.51
Proportion Hispanic	0.03	0.30	0.10	0.02	0.07	0.05	0.13	0.12
Proportion Foreign Born	0.02	0.14	0.07	0.04	0.06	0.13	0.07	0.08
Proportion African American	0.07	0.02	0.06	0.04	0.05	0.04	0.07	0.13

## Chapter 4. Racialized Social Climates in Exceptional Communities

### 4.1 Introduction

For each of the 19 exceptional communities identified in Chapter 3, theoretically relevant predictors of health disparities in LBW cannot fully account for these disparities. These communities have higher or lower rates of black LBW and/or larger or smaller gaps in LBW between babies born to black and white mothers than would be expected given their socioeconomic and demographic characteristics. In this chapter, I use social media data from Twitter to investigate the “racialized social climate” within these communities with a specific focus on anti-black sentiment and other discourses about black folks. I combine machine learning, quantitative, and qualitative analysis techniques to investigate racialized interactions on Twitter, using these data as a proxy for interpersonal (i.e., “face-to-face”) racialized interactions in each exceptional MSA. The results of this analysis suggest that, overall, there is little difference in racialized social climates on Twitter across the exceptional MSAs, regardless of whether they perform “better” or “worse” in regards to the outcomes. That is, the results of this analysis do not offer a definitive explanation to the under- or over-achievement of these MSAs. This finding may be due in part to disagreement between computer and human annotations. However, among the tweets that were considered relevant by both the computer algorithm and human annotators, I find that negative tweets about black people were most common, many of which were also categorized as racist. Results of the thematic analysis also suggest that negative language about black people on Twitter may be gendered, a finding that has potential utility for health research. Taken together, these results suggest that previous research on the association between racialized digital trace data and health may be overstating the amount of data on Twitter and other platforms that is distinctly racist.

## 4.2 Background

Twitter is a popular microblogging social media platform that was launched in 2006 and has been increasing in popularity ever since (Java et al 2007). In the first quarter of 2018, Twitter registered approximately 336 million active users, meaning that these users produced at least one tweet per month, who collectively send more than 500 million tweets per day (Tien 2018). In addition, 46% of users check the network at least once a day. Twitter users engage with the platform and one another through “tweets”, posts that have traditionally been restricted to 140 characters, but as of November 2017 the micro-blogging site now allows tweets of up to 280 characters (Larson 2017). Compared to the US population more broadly, Twitter users are slightly more likely to identify as women than men, tend to be younger (although as the platform ages, so does it’s user population), have similar incomes but tend to be more educated, and are more racially diverse. Of interest to this analysis, while African Americans account for 13.5% of the general population, they represented 26% of the Twitter population (Tien 2018). Of additional interest to this project is the fact that 90% of Twitter users have public profiles, meaning that their tweets can be seen by anyone, anywhere, at any time and that these tweets can be collected from Twitter for research purposes (Nguyen et al. 2019).

People who use Twitter (i.e., “tweeters”) use the platform for various reasons. Research by Marwich and boyd (2011) suggest that Twitter is used a broadcast medium, marketing channel, diary, social platform, and news source. Similarly, Java et al. (2007) find that the main types of intentions for Twitter postings are: daily chatter (talk about daily routines), conversations, sharing information, and reporting the news. Cisneros and Nakayama (2015) note that Twitter is a space of “context collapse” in which tweets are directed to an invisible and “acontextual” audience. While this may be the case, Marwich and boyd (2010) note that Twitter

users do imagine an “ideal” audience (typically a reflection of themselves), actively seek to cultivate authenticity, and may be strategic in what they do or do not share on Twitter for various reasons including privacy and celebrity. In sum, people use Twitter for a variety of reasons, implying that there is no single Twitter user, although patterns of use do seem to emerge.

Of specific interest to this research project is the degree to which behaviors on Twitter are a reflection of behaviors offline. At present, the research on this association is inconclusive. Some researchers suggest that online spaces are “curated” and therefore do not reflect the day-to-day realities of users (Marwick and boyd 2010). Others note that, in regards to stereotypical or violent behavior, people may feel less restricted in these behaviors in online spaces where sanctions may be minimal or non-existent. Indeed, in a time when overtly racist behavior or beliefs seemed to be waning based on national opinion surveys like the GSS, racism on social media appeared to be an exception to this rule. Cisneros and Nakayama (2015) show that Twitter users engage in overt forms of racism online, using Nina Davuluri's Miss America victory as a case. The authors found that Twitter users believed that Davuluri should not be Miss America because she is Arab and Indian and therefore, "not American". Similarly, Rauch and Schanz (2013) note that among the thousands of sites, blogs, and posts that make up social media networks, it is not difficult to find messages that are negative toward a racial minority. Sometimes these messages are subtly negative, but often they are overtly racist. Recently, some Boston Bruin fans made blatantly racist tweets after Joel Ward, who is Black, scored a goal for the Washington Capitals, eliminating the Bruins from the Stanley Cup playoffs. Similarly, an onslaught of racist tweets appeared after the premier of *The Hunger Games* by fans who were upset that one of the main characters was played by a Black actress.

However, there is also evidence to suggest that online behaviors mirror interactions that occur offline. Some research shows that real-time responses (tweets pertaining to things that are happening in real time; live-tweeting) are the most common type of racist tweet. This finding implies that racist tweets are an effect of interactions that occur offline in which individuals engage in racism through social media, rather than offline, interpersonal spaces. Even if no interaction has occurred, tweets may reflect the social climate of a particular area. Focusing on consumer confidence and presidential job approval, O'Connor and colleagues (2010) show that sentiment scores for Twitter data are highly correlated with, and may even be able to replace, opinion polls. In addition, several studies suggest that there is an interaction between what occurs online in spaces like Twitter and offline in a given geographic area. For example, Flores (2017) finds that the implementation of Arizona's SB 1070, a punitive anti-immigration bill, catalyzed twitter users who were already critical of immigrant groups. This relatively small group produced a "spill-over" effect, engaging new users who were significantly more likely to post negative messages about immigrants as well as Hispanics and Mexicans after the passage of SB 1070 than before. While Flores (2017) does not test the effects of these processes on health, research by Anderson and Finch (2014) finds that for Latino residents of Arizona whose primary language is Spanish, there was a significant decrease in reports of self-rated health after the passage of SB 1070. Importantly, these health consequences were limited to residents of Arizona, as states with similar Latino populations but no such legislation did not observe a decrease in health status.

The analysis by Anderson and Finch (2014) is part of a relatively new line of research that takes advantage of extreme events believed to increase negative sentiment towards marginalized groups. For example, Lauderdale (2006) used such methods to predict the risk of

poor infant health outcomes among babies born to Arab women following September 11<sup>th</sup>, 2001. Using birth records, Lauderdale (2006) makes the argument that Arab women experienced an increased period of racial discrimination following September 11<sup>th</sup>, 2001 and hypothesizes that Arab women who gave birth in the six months following the event will have poorer infant health outcomes than Arab women who gave birth six months prior to the event. This hypothesis is confirmed in the case of low birthweight, with babies born to mothers with Arabic names after September 11<sup>th</sup>, 2001 having a higher risk of LBW. This effect was especially pronounced among mothers who gave their children ethnically distinct Arabic names, a proxy for stronger ethnic identification<sup>8</sup>. Likewise, using birth record data for babies born to Latina mothers in Iowa, Novak and colleagues (2017) find that the risk of LBW increased 24% after a federal immigration raid. This finding highlights the widespread effects of racialized immigration policies as the increased risk of LBW was among all Latina mothers in Iowa, regardless of their immigration status.

Studies such as these demonstrate the negative consequences of a racialized social environment on the health of racial minorities in a given geographic area. However, these studies are limited in their generalizability as they are restricted to one event and usually only draw data from one geographic area. As such, researchers have sought novel data sets to test the association between a racialized social climate and health outcomes. Using Google Trends data, Chae et al. (2015) did find a positive association between searches for the “n-word” in a given geographic area and all-cause black mortality in that area. This same metric also predicted the black-white mortality gap. The same group of researchers found that Google Trends data also predict

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<sup>8</sup> Analyses by El-Sayed et al (2008) using a comparable sample of Arab Americans in Michigan found no difference in birth outcomes before and after 9/11. This result further supports the notion that racialized social climates vary across geography and that the racial discrimination experienced by Arab Americans in California may be difference in kind, quantity, and consequence than that experienced by Arab Americans in Michigan.

increases in black preterm birth and LBW across media market areas (Chae et al. 2018). Using data from over 1 million Implicit Association Tests, Leitner and colleagues (2016) also show that as implicit racial bias among whites in a given US county increases, the racial gap in circulatory disease deaths also increases. Recently, Nguyen and colleagues (2018) use Twitter data from 2015-2016 to show that mothers living in states in the lowest tertile of positive sentiment towards blacks had an 8% greater prevalence of low birth weight and very low birth weight, and a 16% greater prevalence of preterm birth, compared to mothers living in states in the highest tertile. Importantly, when the analysis was restricted to just black mothers, the size of the effects did not differ dramatically from those seen in the population. In other words, Nguyen et al (2018) find that anti-black social climates result in negative birth outcomes for babies born to all mothers, not just those who identify as black.

The proceeding analysis builds on the previous research on racialized social climates and health. As Nguyen et al. (2019) note, a social climate with greater hostility towards minorities may cause psychological stress and increase the risk of various negative mental and physical health outcomes as a result. As described in Chapter 1 of this dissertation, we may be able to capture anti-minority sentiment by observing aggregate patterns of socioeconomic inequality, residential segregation, and inequalities in imprisonment, among other processes. While not addressed directly in this dissertation, anti-minority sentiment in a given environment may also be captured through reports of discrimination. Still, as Chapter 2 shows, including a large array of structural measures may not fully explain the gaps in health outcomes between black and white Americans. Using the 19 exceptional communities identified in Chapter 2, I ask the following research questions:

1. Do exceptional communities have higher or lower rates of anti-black sentiment?

## 2. What is the content of anti-black sentiment in these exceptional communities?

### 4.3 Data and Methods

#### 4.3.1 Data Collection

Data for this analysis come from Twitter and is derived from two different sources. First, to build a classifier a team of collaborators and I utilized Twitter's Streaming Application Programming Interface (API) to continuously collect a random sample of publicly available tweets that contained one or more words in a racial lexicon from July 2018-December 2018. The Twitter API is freely available to everyone with a Twitter account and this API allows users free access to a random 1% sample of tweets. We restricted this data collection process to only those tweets containing one or more words or phrases that have been used in previous analyses investigating anti-black sentiment on Twitter (Flores 2017, Nguyen et al. 2018; 2019) as well as additional terms that may capture social conditions that operate as "buffers" (e.g., "Black Lives Matter", "black girl magic", "black boy joy"). The search terms used in this data collection process are shown in Table 4.1. This initial data collection process produced 2117 unique tweets that would be used to develop our classifier.

Second, to test the validity of our classifier and to measure racialized social climates in each of the 19 exceptional MSAs, I collected historical, geocoded Twitter data from the Digital OnLine Life and You (DOLLY) Project. DOLLY is a repository of billions of geo-located tweets that allows for real-time research and analysis. Twitter data from DOLLY contain latitudinal (y) and longitudinal (x) coordinates in addition to data on screen name, number of followers, hashtags used, and the text of each tweet. This level of geographic specificity allows for data aggregation at any level, including the county and MSA-levels, therefore making DOLLY a worthwhile data set for examining racialized social climates. For this second data collection

process, I retrieved all tweets in the DOLLY data set from 2012-2016 for the 19 exceptional MSAs identified in Chapter 2. This data collection process produced approximately 8.93 million unique tweets.

#### 4.3.2 Computer Modeling and Quantitative Analysis

The first step in my analysis was to develop a classifier that could categorize tweets using machine learning techniques. Using the 2117 unique tweets collected from the streaming API, my team of collaborators and I analyzed a subsample of 100 tweets and developed a coding scheme that would identify a tweet as positive or negative using a Likert scale, as racist, anti-racist, or empowering, and as about black people, black women, or black men. While this coding structure was informed by the collective goals of the research team, two codes were intended specifically for this project. First, the use of the “anti-racist” and “empowering” codes were intended to capture positive discourse about black folks on Twitter and identify social climates that could mitigate the negative effects of racism. Second, the identification of the subject of a tweet as black people, black men, or black women was intended to capture differences in discourses that were about black people in general or about black men or black women in particular. Since the majority of people who will give birth identify as women, it is worthwhile to identify racialized *and* gendered social climates.

Once we had established a coding scheme, we used the Amazon Mechanical Turk (MTurk) platform to collect human annotations for a subset of tweets. We chose to use MTurk for this task as opposed to relying on our research team for two primary reasons. First, we wanted to test the validity of our instrument on a new set of raters. Second, we hoped to increase the variability in the demographic characteristics of raters since our research term is restricted in age, gender, race, and other sociodemographic characteristics that may influence ratings. Using

the online tool shown in Figure 4.1, MTurkers (i.e., individuals who complete tasks on MTurk) were instructed to provide categorical ratings for the content of the tweet (e.g., racist, anti-racist, or empowering) and an ordinal rating for the polarity of the tweet (i.e., -3 “Very Negative” to +3 “Very Positive”). In addition, we included an open-ended ‘notes’ field to provide space for comment on tweet ratings that would appear once MTurkers had completed the task. We collected responses from 38 individual MTurkers<sup>9</sup> who analyzed a total of 54 separate tweets, producing 1108 codes<sup>10</sup>.

Next, my collaborators and I used the MTurk annotations to train a computer algorithm to analyze the tweets from DOLLY. The computer algorithm uses the labeled tweets to learn what humans consider a “positive”, “negative”, or “neutral” tweet, what tweets are about “black people”, “black women”, or “black men”, and what tweets are considered “racist”, “anti-racist”, or “empowering”. Once trained, the computer algorithm can use these labels to categorize the sample of 8.93 million tweets from DOLLY based on various specifications. Preliminary analyses revealed that the algorithm’s accuracy against manual annotations from MTurk was relatively low in regards to categorizing tweets about black people, black men, or black women. That is, the algorithm was unable to identify the “true” subject of the tweets, assuming that human annotations were “correct”, at a rate that was greater than chance. In addition, the algorithm performed poorly in categorizing tweets as racist, anti-racist, or empowering, likely due to the poor levels of interrater agreement between MTurks. However, our algorithm performed relatively well in regards to sentiment (e.g., positive, negative, and neutral).

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<sup>9</sup> While previous research tends to employ larger numbers of MTurkers, we chose to pay \$15/hour for our task, thereby limiting funds to allocate to MTurks. However, based on research on the systematic exploitation of MTurk labor, we feel that this was a worthwhile tradeoff.

<sup>10</sup> Due to funding and time constraints, MTurk ratings were done in two “batches”. The first batch included ratings from 10 individual MTurkers for 24 separate tweets. The second batch included ratings for 28 individual MTurkers for 31 separate tweets.

Given the performance of our classifier, we categorized all tweets in the DOLLY sample as either about black people or not and as either positive, negative, or neutral. The computer algorithm identified 33760 unique tweets as being “about black people” and identified 3757 of those tweets as positive, 22060 as neutral, and 7943 as negative from the universe of 8.93 million tweets across the 19 exceptional MSAs available through DOLLY. These 33760 tweets were merged with sociodemographic and population characteristics in each MSA and analyzed for associations between exceptional MSAs and the sentiment of tweets that were categorized as “about black people”.

#### 4.3.4 Qualitative Analysis

The next step in my analysis is to qualitatively analyze a subset of tweets from the DOLLY sample. The goal of this qualitative analysis is two-fold. First, human annotations will help evaluate the accuracy of the computer algorithm. This iterative process of computer modeling and human annotations is a necessary step in the “text as data pipeline” and helps identify the shortcomings of computer models. Second, thematic analysis identifies the content of tweets and may provide insights into the racialized social conditions individuals experience in off-line spaces.

From the subsample of 33760 tweets that our classifier identified as “about black people”, I extracted a random sample of 40 positive tweets, 40 negative tweets, and 40 neutral tweets from each of the 19 exceptional MSAs, for a total of 120 tweets per MSA to be used in qualitative analysis. The 2280 tweets selected in this process make up the qualitative analytic subsample. From this subsample, a team of undergraduate researchers (UGRs) and I developed a codebook and applied thematic analysis techniques to identify the content of tweets about black people across MSAs.

The first step in a qualitative thematic analysis is to develop a codebook. For this research project, several focused codes had already been established by my collaborators and I prior to analysis by the UGRs. These codes were used when collecting human annotations from MTurkers and are shown in rows 2-10 in Table 4.2. The remaining codes, shown in rows 1 and 11-19 were developed by the UGRs and myself. UGRs were given a 10% random sample (N = 228) of the qualitative twitter data to use for codebook development. Following the methodology outlined by Braun and Clarke (2006), UGRs were instructed to first read through all 228 tweets without taking notes or making codes. Second, they were instructed to read through the data again and begin taking notes and creating codes as they went. Third, they were instructed to review their codes and combine codes when possible, renaming them if necessary. Fourth, they were instructed to review their final codes in groups of four, eliminating, combining, and renaming codes when necessary, if at all. Finally, I lead the UGRs in a codebook development exercise until all codes and concepts had been included. For each code, students provided the name of the code, the properties of the code, and an example tweet to guide their classmates in the coding process.

Once codebook development was complete, the next step in our analysis was to apply our codes to the full qualitative analytic sample of 2280 tweets. To do this, I divided the data into five equal subsamples, each containing 456 tweets. I then divided the UGRs into five groups and assigned each group to a subsample of 456 tweets. UGRs independently coded all assigned tweets using the focused codes shown in Table 1.2. UGRs were also instructed to code all relevant codes for a given tweet and to offer additional codes if need be. Once coding was complete, UGRs compared codes in groups and where allowed to alter their original codes if need be, although they were not required to make any changes. Once comparison was complete,

UGRs finalized their thematic analyses and produced research memos. Both the codes and the memos are treated as sources of data in this analysis.

#### 4.4 Results

##### 4.4.1 Quantitative Results

Below, I describe results from the quantitative analysis, based on the computer algorithm classification of the subject and sentiment of tweets in the DOLLY sample. As noted above, 33760 tweets from the DOLLY sample were identified as “about black people”. Among those, 3757 tweets were identified as positive, 22060 as neutral, and 7943 as negative. Table 4.3 shows the rate of positive, negative, and neutral tweets about black people for each MSA that is identified as exceptional in regards to the black LBW rate. From the results in Table 4.3 it is clear that the majority of tweets the computer algorithm identified as “about black people” were also categorized as having a neutral sentiment. In addition, across all MSAs, it is clear that of the tweets about black people that are not neutral, more tweets are negative than positive. This is true for MSAs with higher and lower rates of LBW than expected given the sociodemographic characteristics of these communities. However, a few MSAs appear to stand out. Specifically, Ithaca, New York which has both a higher black LBW rate and a bigger black-white gap in LBW has the highest rate of negative tweets as well, with 32% of all tweets that were classified as about black people in Ithaca being categorized as negative as well. In addition, Beckley, West Virginia, an MSA with lower rates of black LBW rate than expected, has the highest rate of positive tweets about black people of any MSA (13.54%). However, they also have the highest proportion of negative tweets about black people of the “better than expected” MSAs, implying that the racialized social climate in Beckley may be more polarized than in the other exceptional MSAs.

Table 4.4 shows the rate of positive, negative, and neutral tweets about black people for each MSA that is identified as exceptional in regards to the black-white LBW ratio. As was the case for the results in Table 4.3, the majority of tweets about black people have a neutral sentiment, followed by negative tweets. Positive tweets appear the least. As was also the case in Table 4.3, MSAs that have smaller black-white gap in LBW than expected do not necessarily have a smaller proportion of negative tweets about black people. While the Ithaca, NY MSA still has the highest proportion of negative tweets about black people, it is followed by the Vineland-Bridgeton, New Jersey MSA which actually has a smaller black-white gap in LBW than expected. In addition, Ocean City, New Jersey and Midland, Texas have the highest proportion of positive tweets across the exceptional MSAs in Table 4.4, yet both are categorized as have larger black-white gap in LBW than expected.

The results in Tables 4.3 and 4.4 suggest that there is little difference in racialized social climates across MSAs. However, computer algorithms can only learn from the information they are given. As such, it is a possibility that the algorithm incorrectly categorized tweets or that the algorithm was unable to pick up on nuanced discussions or race, sarcasm, or other forms of communication that may bias results. To investigate these possibilities and to describe the content of tweets, I turn to the qualitative analysis results.

#### 4.4.2 Comparison of UGR codes and Computer Codes

Comparisons between student UGR codes and computer codes imply that there is a considerable amount of disagreement between the two sets of codes. Before comparing codes, I processed the UGR codes such that if three or more raters agreed on a code, that code was considered valid. For example, if three of the five students who coded tweet #1585, “see monkeys [aren’t] that different than [us we] have a monkey as a ring leader of a president” as

racist, then the tweet was considered to be racist. Since every tweet was rated by five UGRs, this ensured that at least half of the UGRs who coded a given tweet agreed on the codes applied to that tweet. Comparisons of sentiment ratings are shown in Table 4.5.

The results in Table 4.5 show that sentiment agreement between UGRs and the computer algorithm were very low. For example, among the tweets that the computer identified as “positive”, UGRs considered less than one percent of these tweets to have the same sentiment. In fact, among the 755 tweets the computer algorithm identified as positive, UGRs coded nearly 10% of these same tweets as “negative”. An example of a tweet that was identified by the computer as “positive” but considered “negative” by students is tweet #151648: *“Really respect the way Dani Alves handled himself today Probably not too easy to have people throw bananas at you and call you a monkey”*. This particular tweet is referencing a 2014 incident in which bananas were thrown at Dani Alves, a soccer player from Brazil. Alves responded by picking up the banana and taking a bite before completing a corner kick. This tweet demonstrates the difficulty of using Twitter data to measure racialized social climates. This tweet is recounting a racialized incident that occurred in Spain, not in one of the exceptional MSAs analyzed here. However, a person tweeting from one of these MSAs is referencing the incident and appears to be expressing positive affect for Alves while simultaneously expressing negative affect for the incident. As such, the computer algorithm correctly identified the sentiment of the person tweeting, while UGRs correctly identified the sentiment of the incident.

Another key finding shown in Table 4.5 is that the majority of tweets in the qualitative analytic subsample are regarded by UGRs as “not relevant”. Given that one of the main goals of collection of human annotations from UGRs was to fine tune the algorithm, I did not restrict the qualitative analytic subsample based on accuracy. While the computer algorithm provides an

accuracy statistic for both the sentiment and subject of the tweet, it is potentially worthwhile to include even those tweets with low accuracy in the qualitative analytic subsample as UGRs may bring with them knowledge of topics that the computer algorithm was not trained to identify. This was the case for tweets about musicians, tweets that included song lyrics, and tweets that used slang terms.

While this specialized knowledge was useful in some cases, UGRs coded less than 15% of the 2265 tweets in the qualitative subsample as “about black people”. However, a closer inspection of this disagreement shows that both the UGRs and the computer may have failed to properly identify the subject of the tweet. For example, tweet #3351: “*I wanna rewrite my friend list See dis is why I need my black book Ugh I should be sleep*” was identified by the computer algorithm as “about black people” and had a high accuracy rating of 0.8706. However, UGRs did not code this tweet as “about black people”. Indeed, the subject of this tweet appears to have nothing to do with black people, indicating a failure of the computer algorithm. In contrast, tweet #11944: “*Your BS is killing our country you fucking monkey get out now Go back to Africa We didnt want you here*”, while identified by the computer algorithm as about black people with an accuracy ration of 0.4168, UGRs did not consider this tweet to be “about black people”. However, UGRs did code this tweet as “racist”, including “racial language and slurs”, and as “negative”. This implies a failure among the UGRs to include all relevant codes in their coding analysis.

#### 4.4.3 Overview of UGR Coding Results

The degree to which UGRs applied each code across the 2265 tweets in the qualitative subsample is show in Table 4.6. As was noted in Table 4.5, “not relevant” is the most common code in the dataset as UGRs applied this code to nearly 61.0 percent of all tweets. The second

most common code was “black people”, which was applied to 15.0 percent of all tweets. While it is not surprising that this code was applied relatively often, given that all tweets analyzed by UGRs were identified by the computer algorithm as “about black people”, it is surprising how few tweets were coded by the UGRs as such. UGRs coded approximately 4.0 percent of tweets as about black women and an additional 4.0 percent of tweets as about black men. Among those tweets that were coded for sentiment, the most common code was “negative”, which was applied to almost 6.0 percent of all tweets. Based on the selection of the qualitative sample, we would expect that 33.0 percent of all tweets would be coded as negative. However, as was noted in the previous section, there appears to be a high degree of disagreement between the computer algorithm and the UGR codes.

Table 4.7 shows the degree to which certain codes co-occurred in the data set. From these results it is clear that while some UGRs chose to co-code the subjects of the tweets (e.g., black people, black women, black men), this was not necessarily a common approach. Taking co-coding into consideration, 462 individual tweets, approximately 20.4 percent of the qualitative subsample were categorized as about black men, about black women, or about black people. Tweets about black people in general were most often co-coded as racist (N = 41), negative (N = 66), and generalizations or stereotypes (N = 50). Tweets about black women were most likely to be co-coded as generalizations or stereotypes (N = 29), negative (N = 22), and positive (N = 12). Tweets about black men followed a similar pattern. Tweets identified by UGRs as racist were also likely to be coded as negative (N = 53), include a racial slur (N = 31), and include a generalization or stereotype (N = 20). Tweets that were coded as “anti-racist” were rare, as were “empowering” tweets. However, 12 tweets were coded as both “positive” and “empowering”. Lastly, of the 129 tweets that were coded as “negative”, 53 were also identified as racist, 32

contained racial language or slurs, and 30 of these negative tweets contained generalizations or stereotypes.

#### 4.4.4 Thematic Analysis

In this section, I choose to review the results of the thematic analysis collectively, rather than dividing the analysis by MSAs that are categorized as over- or under-achievers in regards to the outcome. As noted above, MSAs did not differ drastically in the proportion of negative or positive tweets about black people. In addition, previous research by Nguyen et al. (2018; 2019) seeks to understand the content of racism on Twitter rather than compare the differences in how racism presents itself in online spaces across geography. For these reasons, I describe themes identified by UGRs broadly, providing examples when necessary. In addition, I describe the coding decisions made by UGRs and noted in their research memos as well as my own classroom observation notes. Given the lack of research on how human annotators decide if a tweet is racialized or not, these methodological notes are a critical contribution to the body of research on racism in online spaces.

As noted in previous sections, much of the data was identified by the UGRs as “not relevant” meaning that the tweet was not about black people and therefore, not relevant to the scope of this project. For example, the tweet, “*atwitterhandle atwitterhandle ikr our Black Friday is gonna be mainly on Thursday so that’s why everyone has to work that day*” is an exchange between people on Twitter about the day after Thanksgiving in the US, also known as Black Friday. Similarly, many tweets in the qualitative subsample were describing “black coffee”, “black dresses” and “smoking blacks” (i.e., Black & Mild cigars) and did not include any words or phrases to indicate the subject of the tweet was black people. These examples

demonstrate the failure of the computer algorithm to pick up on these differences in the DOLLY data set.

In regards to whether a tweet was considered racist or not, UGRs noted that they would make this decision based on the presence of racial slurs, stereotypes or a general negative sentiment towards black folks. For example, tweet #144339: *“Thats why I looked straight ahead I was telling myself dont look dont look hes black Hes for sure thug atwitterhandle”* implies that black men (or, at the very least this particular black man) are dangerous and that the person tweeting had to adjust their behavior when in close proximity to this person. For some students, the presence of the “n-word”, particularly if it ended in “-er” was enough to categorize that tweet as racist. For example, the tweet, *“I find it funny that this [n-word] sophomore in high school is verbally running circles around a freshman in college”*, was coded by one UGR as racist not necessarily because of the sentiment of the tweet, which could be interpreted as positive or negative, but because a racial slur appeared in the text. One UGR who identifies as black noted that seeing the n-word ending in “-er” is particularly triggering, regardless of how it is being used by the speaker.

Several UGRs noted that a simple classification of “racist” did not fully capture the nuances of some tweets in the dataset. For example, the tweet, *“Dont attack me I love black people”*, includes certain phrases that could be regarded as negative (“attack”) as well as phrases that could be regarded as positive (“love”), and is clearly about black people. However, the phrase as a whole evokes a type of covert racism that defends one’s own race relations. The author is implying that they shouldn’t be “attacked”, perhaps as a result of a racialized comment they made, because they “love black people”. UGRs noted that this and other tweets like it

include elements of defensiveness and ignorance not fully captured by the “racist” code or other codes in the dataset.

Decisions about the sentiment of the tweet proceeded in a similar fashion. Negative sentiments were identified most often. When applying this code, some students took a holistic approach and attempted to assess the feeling and emotion of the tweet rather than the use of slurs, stereotypes, or generalizations alone. For example, the tweet, “*Cant believe people are still shocked that an 80 year old white billionaire doesn’t like blacks*” implies a sense of frustration and perhaps even exhaustion that people would be surprised about racist remarks made by LA Clippers owner Donald Sterling in 2015. Interestingly, other tweets about the same incident were regarded by other UGRs as neutral including tweet #153580: “*I hope everybody realizes this is far deeper than sterling saying he didnt want his gf bringing black people to games.*” UGRs noted that based on this tweet alone and in the absence of more context, it was unclear whether the author of this tweet felt negatively or positively about the incident with Donald Sterling. Instead, this tweet read as a flat statement.

Thematic analysis also uncovered the differential use of language in tweets about black men compared to tweets about black women. As noted in Table 4.7 tweets about black women were slightly more likely to use generalizations or stereotypes and to be categorized as negative by UGRs than tweets about black men. In addition, UGRs were more likely to apply co-codes to tweets about black women than those that were coded as exclusively about black men. These differences may be due to the lack of ambiguity in tweets about black women, as negative tweets about black women tended to be perceived as more pointed than those about black men. For example, the tweet, “*I dont call women bitches but yall Black women are about to change that*”, implies that the author is so upset by black women as a whole that they are considering using a

phrase they currently consider taboo and perhaps applying that term to black women exclusively. However, some UGRs noted that themes of violence and aggression were regularly applied to black men but that this was not necessarily the case for tweets about black women. When combined with the “hypersexualization” theme, the differences between tweets about black men and black women were particularly striking. In general, the hypersexualization theme only applied to 30 tweets, 7 of which were identified as about black people in general, 5 of which were coded as about black women, and 7 of which were coded as about black men. While both tweets about black men and black women fetishized black bodies and specific body parts, tweets about black men often implied that black men were sexually aggressive, particularly towards white women.

While the thematic results provide rich description of the content of tweets about black people across exceptional MSAs, interpreting tweets without context proved difficult. For example, tweet #1880097, “atwitterhandle *For Black History Month I encourage all girls to take their weave out get in touch with your roots*” is a complex sentence that can be interpreted several ways in the absence of context or based on the characteristics of the person coding the tweet. As one UGR wrote in their memo:

*“This tweet was confusing because I couldn’t tell if they were just stereotyping that all African American women wear weaves and should “get in touch” with their roots implying that they are not proud of their own hair. I personally found this tweet offensive because African American women can do anything they want with their hair, if they want to wear weaves, what is the big deal? When African American women wear their natural hair they are portrayed as unprofessional so seeing this tweet annoyed me.”*

In this example, the UGR is grappling to make sense of the intent and consequences of this tweet. Ultimately, they determine that this tweet is harmful but notes that knowing the race of the person tweeting would have been helpful in determining how they felt about the content of the tweet. Other UGRs noted that they would have liked to see images and hyperlinks as well as

usernames to help make sense of the language used in several tweets. While these pieces of information were either not available in DOLLY or removed in pre-processing for computational analysis, coding tweets without this information proved challenging.

Another challenge UGRs faced was their own positionality or intent in analyzing these data. Non-black and non-white students had a difficult time identifying certain codes and themes in comparison to their peers. Notably, the “ignorant or bad humor” code was developed by a black student during codebook development and was more likely to be used by non-white students who could detect covert forms of racism and microaggressions. For example, tweet #486941, “*some black chick is going to twerk her way into my heart*” and tweet #1612033: “*atwitterhandle Black people will sacrifice their light bill to buy a Gucci belt to flex for instagram*” were coded by non-white students as bad jokes that relied on stereotypes about black people. Similarly, students felt ill equipped to analyze tweets based on their lack of knowledge of certain phrases, of the culture and norms of behavior on Twitter, and of historical events that would help place certain statements in context. For example, a tweet that requires several types of specialized knowledge to interpret is tweet #130065, “*Obama AbortionPresident sides w Racially Motivated PLANNED PARENTHOOD 2 kill Black Babies as their founder Margaret Sanger POPULARIZED*”. While Margaret Sanger, the founder of Planned Parenthood, was motivated by the eugenics movement to start the organization, this is no longer the *modus operandi* of Planned Parenthood. However, political conservatives often evoke this fact in an effort to stigmatize abortions and Planned Parenthood. Tweets such as these are complex and rely on knowledge of historical and contemporary processes for interpretation. It is unclear whether human annotators or computer algorithms would be able to decipher this degree of complexity.

#### 4.5 Discussion and Conclusion

The goal of this multimethod analysis is to identify the quantity and content of racialized language on Twitter and investigate the utility of this data as a proxy for racialized social climates that may influence health inequalities between black and white Americans. Based on the results presented above, it does not seem that MSAs with exceptionally low black LBW rates and/or exceptionally small black-white gaps in LBW have more or less positive or negative racialized language among Twitter users in these MSAs than those communities with exceptionally high black LBW rates and/or exceptionally large black-white gaps in LBW. That is, based on the results of this analysis, Twitter does not appear to be a useful tool for capturing social conditions that produce “routes” to low birth weight.

This conclusion contradicts two previous studies that use digital trace data to investigate the association between racialized language in online spaces and racial disparities in LBW. First, Chae et al. (2018) use data from Google Trends to measure “area-racism” as the proportion of search queries containing the “n-word” (singular or plural, ending in “-er” or “-ers”, excluding variants ending in “-a” or “-as”) from 2004 to 2007. They aggregate this measure to designated market area (DMA) and find that each standard deviation increase in area racism was associated with a relative increase of 5% in the prevalence of low birthweight among babies born to black mothers, net of relevant individual and county-level confounders for LBW. Second, Nguyen et al. (2018) use data from the Twitter API to measure minority sentiment at the state level based on the proportion of tweets that expressed a positive or negative/neutral sentiment about various racial and ethnic groups. Regression analyses suggest that infants born in states with lower levels of positive sentiment towards racial minorities are at an elevated risk for LBW but that the odds of LBW does not vary based on the race of the mother. Of particular interest was the finding that

the associations between sentiment towards blacks and birth outcomes of black mothers were not different from the associations between sentiment towards blacks and birth outcomes in the full population of mothers.

The quantitative analyses presented here build upon the research by Chae et al. (2018) and Nguyen et al. (2018) in several ways. First, I use keyword searches for 28 terms or phrases related to black Americans to collect Twitter data to build a classifier with. Like Nguyen and colleagues (2018) this goes beyond keyword searches for a single racial slur but unlike Nguyen et al. (2018) I integrate phrases that may signal resilience and positive sentiment about black Americans (e.g., “black lives matter”, “black boy girl”, “black girl magic”). Second, I distinguish between tweets about black people in general and black men or women in particular. While this approach requires adjustment to improve both computer and human annotations, results of the thematic analysis suggest that racialized language on Twitter is also gendered in a distinct way that may be useful for understanding variation in the risk of LBW between black and white mothers. While Nguyen et al. (2019) include thematic analysis in a related study using the same data set, they categorize language related to physical appearance and sexuality as outside of the “spectrum of negativity”. While some tweets with this type of content may be innocuous, it is also the case that language on Twitter sexualizes black people in a way that is derogatory, negative, and overtly or covertly racist.

Third, I incorporate data from a broader time frame (2012-2016) and at a lower level of geographic aggregation. While reducing the level of aggregation to the MSA limits the quantity of data available for analysis, higher degrees of aggregation such as the DMA or state may miss important variation in racial sentiment. In addition, while Chae et al. (2018) and Nguyen et al. (2018) frame their analysis on the assumption racialized language in online spaces operates as a

proxy for experiences of racial discrimination (the same stance that I take here), large areas of aggregation may not be theoretically appropriate. For example, it is unlikely that tweets about black people sent by users in New York City provide an accurate proxy for the racial discrimination experienced by black people in Ithaca, New York. Indeed, while I find that Ithaca, New York has an exceptionally high rate of negative tweets about black people, Nguyen et al. (2018) find that the state of New York has some of the highest rates of positive tweets about black people. Fourth, and relatedly, the twitter data analyzed here come from MSAs that were identified as outliers based on theoretically-informed quantitative analyses. While this approach narrows the scope of the analysis, it goes beyond data-driven associational studies to consider the ways in which racialized language on Twitter relates to structural measures of racial inequalities within MSAs. In addition, the regression models used to identify exceptional MSAs include a more robust set of area-level covariates than the analysis by Nguyen et al. (2019), a potential explanation for the lack of variation in the association between racialized language on Twitter and birth outcomes across racial and ethnic groups.

This discussion suggests that previous analyses may be overestimating the association between racialized language in online spaces and the likelihood of LBW. While digital trace data in general, and Twitter data in particular, may hold many promises for health research, these tools have yet to be fully calibrated. Quantitative analyses suggest that Twitter data produce a high degree of “noise”, even when aspects of text such as racial slurs are taken into consideration. Thematic analyses suggest that tweets about black people are more likely to be negative than positive and that many of these tweets are also considered racist by human annotators. Notes on coding decisions by UGRs provide critical insight into how human annotators make decisions about what is or is not considered racist and there is some evidence to

suggest that this interpretation, unsurprisingly, varies by race. Lastly, this study suggests that taking an intersectional approach to the analysis of racialized language on social media would be worthwhile, particularly when investigating health outcomes that are more likely to occur among people who identify as women.

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## Main rating screen

Look at the tweet or tweet conversation. Use the sentiment rater to evaluate the sentiment the tweet presents.

**Check all applicable topics**

- Black Men
- Black Women
- Black People

**Check all applicable topics**

- Racist
- Anti-Racist
- Empowering

**Sentiment Rating towards black people**

- Very Negative
- Somewhat Negative
- Mildly Negative
- Neutral
- Mildly Positive
- Somewhat Positive
- Very Positive

### Tweet #1

 **cornell Stanley**  @stanleycornell1 · Jun 30, 2018

So wa e mean

 **lingling**  @IndiaGadsden1

To me pro black means wanting black people to be better as a whole. Just uplifting black ppl w out bashing white ppl but when i say things blacklivesmatter or black girl magic assume "I'm anti-white" but I'm not

♥ 1 2:57 PM - Jun 30, 2018

[See lingling's other Tweets](#)

### Tweet Text:

@stanleycornell1 To me pro black means wanting black people to be better as a whole. Just uplifting black ppl w out bashing white ppl but when i say things blacklivesmatter or black girl magic assume "I'm anti-white" but I'm not

Figure 4.1. Screen Capture of “Tweet Rater” Provided to MTurkers

**Table 4.1. Final Racial Lexicon for Keyword Searches**

nigger	African-American	“black dude”	“black lives matter”
niggress	blacks	“black men”	BLM
“porch monkey”	AfricanAmerican	“black female”	“black girl magic”
race-baiter	"black people"	“black man”	blackgirlmagic
race-bait	"black ppl"	“black male”	blackboyjoy
“race baiter”	"black guy"	“black women”	“black boy”
"race baiting"	“black girl”	“black lives”	“black boy joy”

<b>Table 4.2. Codebook for Twitter Data</b>		
Code	Properties	Example Tweet
Not Relevant	Tweet does not appear relevant to the goals of this research project (i.e., the tweet is not about black people)	"A fun time with black coffee devo and soft smiles"
Black people	The tweet is clearly about black people. This can reference a specific black person or reference black people as a group	"I hope everybody realizes this is far deeper than sterling saying he didnt want his gf bringing black people to games"
Black women	The tweet is clearly about black women. This can reference a specific black woman or reference black women as a group	"Now I know why Im scared of these black women"
Black men	The tweet is clearly about black men. This can reference a specific black man or reference black men as a group	"These white babies walking around LL look at Richi like they never seen a black man Tell me why this is good"
Empowering	Describe social, political, and economic empowerment of African Americans (e.g., scholarships, awards, community events, solidarity, general pride)	"Thank you @theadvocateno for highlighting the #gustaveblacheartscholarship that will send two #AfricanAmerican students from Louisiana to The School of Visual Arts in #ny for undergraduate and graduate degrees. @SVA_News @svanycalumni @KnowLouisiana #college #nola #sva #art"
		"Black women be outchea!!!!!! 🍆🍆🍆"
Racist	Describes overtly or covertly racist language such as stereotypes, derogatory language, and racial slurs. References to violence and reverse racism as shown here also qualify.	"@thehill These black people hate white Americans.They race bait they incite they relish being a victim."
		"I'm very happy POTUS decided to start releasing the coup documents. Now release everything. All of it. Burn down the Obama administration and hang 'em high"
Anti-racist	Disqualifies or challenges racist behavior either directly or indirectly/globally. Sheds light on and calls out racialized behaviors, policies, etc.	"Shit like this will never be funny to me... black people are being shot and killed for shit not even close to this"
		"Lool ppl are acc so racist and don't even clock...everyone chatting shit abt Samira saying the typical tings "aggressive", "angry".STFU ppl too quick to associate black ppl with them qualities..it's old now"
Positive	The tweet has a clearly positive sentiment (can and may overlap with other categories)	"cuz Im a strong independent black woman"
Negative	The tweet has a clearly negative sentiment (can and may overlap with other categories)	"Does anyone remember that mean black lady sub we had in biotech that was the biggest bitch ever LOL"
Neutral	The tweet is not clearly negative or positive (can and may overlap with other categories)	"african american"
Racial language or slurs	Tweet contains a racial slur	"What a [n-word]"
Generalizations/ stereotypes	Tweet has generalization or stereotypes about any group of people (e.g., black folx, white folx, etc.)	"Black kids birthday parties be like"
Political	Tweets related to politics (e.g., government, organizations, protests, police, specific events and people)	"Ferguson Unanimous decision by Grand Jury including blacks Overwhelming evidence including testimony from 60 witnesses How is this wrong"

Hyper-sexualization	Tweet mentions sexualization of black folk, mentions specific body parts	"I like my women how I like my coffee black And without a penis"
Ignorant/Bad Humor	Tweet contains contains racially charged language that is not reflexive, has marked language (explicitly names non-white groups)	"is saying [n-word] lip racist"
		"Black white Asian etc If your hot your hot"
Ambiguous	Tweet contains racially charged language but without context is hard to interpret	"Monkey awebsite"
Racial Comparison	Tweet makes interracial or intraracial comparisons	"Can atwitterhandle do one on African amp BlackAmericans always hating on each other And No African girls dont care if you date our men"
Cultural Appropriation	Tweet appears to appropriate black culture and language or mentions cultural appropriation by others (may or may not overlap with the "ambiguous" tweet as whether the tweet is appropriative or not would depend on the context/who the tweeter is)	"Im just gonna join a black fraternity"
		"Srsly though in reIggy Azaleahistory of American pop culture is the dialectic of black innovationblackfacethats it the whole thing"
Other - <b>Please list the themes</b>	Content of tweet is not captured by any of the codes above	<b>IF YOU USE THIS CODE BE SURE TO EXPLICITLY NAME YOUR NEW CODE(S)</b>

**Table 4.3. Sentiment of Tweets about Black People for MSAs with Exceptional Black LBW Rates**

	Black LBW Rate	Predicted Value	Proportion Positive Tweets	Proportion Neutral Tweets	Proportion Negative Tweets
<b>BETTER THAN EXPECTED</b>					
<i>Kokomo, IN</i>	<i>0.0247</i>	<i>0.0581</i>	<i>0.1146</i>	<i>0.6788</i>	<i>0.2066</i>
<i>Kennewick-Richland, WA</i>	<i>0.0123</i>	<i>0.0395</i>	<i>0.1199</i>	<i>0.6473</i>	<i>0.2328</i>
Beckley, WV	0.0388	0.0609	0.1354	0.6238	0.2408
<i>Kingston, NY</i>	<i>0.0280</i>	<i>0.0484</i>	<i>0.1132</i>	<i>0.6730</i>	<i>0.2138</i>
<i>Morgantown, WV</i>	<i>0.0404</i>	<i>0.0585</i>	<i>0.1071</i>	<i>0.6744</i>	<i>0.2185</i>
<b>WORSE THAN EXPECTED</b>					
Fort Smith, AR-OK	0.0649	0.0476	0.1218	0.6601	0.2182
Owensboro, KY	0.0617	0.0445	<i>0.1160</i>	<i>0.6624</i>	<i>0.2216</i>
Alexandria, LA	0.0792	0.0610	<i>0.1281</i>	<i>0.6295</i>	<i>0.2424</i>
<i>Ocean City, NJ</i>	<i>0.0611</i>	<i>0.0401</i>	<i>0.1255</i>	<i>0.6409</i>	<i>0.2335</i>
Wheeling, WV-OH	0.0741	0.0505	0.1242	0.6769	0.1989
<i>Ithaca, NY</i>	<i>0.0667</i>	<i>0.0393</i>	<i>0.0836</i>	<i>0.5921</i>	<i>0.3243</i>
Sierra Vista-Douglas, AZ	0.0806	0.0498	0.1033	0.6568	0.2399
Johnstown, PA	0.0873	0.0527	0.1244	0.6742	0.2014

*Note:* MSAs with standardized residuals 2 standard deviations above or below the mean for both outcomes are shown in italics.

**Table 4.4. Sentiment of Tweets about Black People for MSAs with Exceptional Black-White LBW Ratios**

	Black-White LBW Ratio	Predicted Value	Proportion Positive Tweets	Proportion Neutral Tweets	Proportion Negative Tweets
<b>BETTER THAN EXPECTED</b>					
<i>Kokomo, IN</i>	<i>0.9602</i>	<i>2.5255</i>	<i>0.1146</i>	<i>0.6788</i>	<i>0.2066</i>
<i>Kennewick-Richland, WA</i>	<i>0.7383</i>	<i>2.2786</i>	<i>0.1199</i>	<i>0.6473</i>	<i>0.2328</i>
Vineland-Bridgeton, NJ	1.4604	2.5308	0.1237	0.6192	0.2571
<i>Kingston, NY</i>	<i>0.9251</i>	<i>1.9819</i>	<i>0.1132</i>	<i>0.6730</i>	<i>0.2138</i>
<i>Morgantown, WV</i>	<i>1.0102</i>	<i>1.9568</i>	<i>0.1071</i>	<i>0.6744</i>	<i>0.2185</i>
<b>WORSE THAN EXPECTED</b>					
Midland, TX	3.3433	2.3862	0.1262	0.6604	0.2135
Oxnard-Thousand Oaks-Ventura, CA	2.8218	1.7678	0.0993	0.6637	0.2370
Bloomington, IN	2.9242	1.8823	0.1092	0.6488	0.2420
Kankakee, IL	3.9926	2.5533	0.1086	0.6516	0.2398
San Luis Obispo-Paso Robles-Arroyo Grande, CA	3.6346	2.2131	0.0890	0.6637	0.2370
<i>Ocean City, NJ</i>	<i>4.5755</i>	<i>2.2180</i>	<i>0.1255</i>	<i>0.6409</i>	<i>0.2335</i>
<i>Ithaca, NY</i>	<i>5.6581</i>	<i>2.5384</i>	<i>0.0836</i>	<i>0.5921</i>	<i>0.3243</i>

*Note:* MSAs with standardized residuals 2 standard deviations above or below the mean for both outcomes are shown in italics.

**Table 4.5. Comparison of Sentiment Ratings from UGRs and Computer Algorithm**

<i>Student Rated Sentiment</i>	<i>Computer Rated Sentiment</i>		
	<b>Positive</b>	<b>Negative</b>	<b>Neutral</b>
Positive	0.0079	0.0359	0.0211
Negative	0.0967	0.0386	0.0356
Neutral	0.0106	0.0173	0.0224
Not Relevant	0.5550	0.6090	0.6649
N	755	752	758

*Note:* 15 tweets received no codes from UGRs and were excluded from this portion of the analysis (N = 2265). Due to errors in UGR annotations and disagreement in coding among UGRs, proportions shown in columns do not necessarily sum to 1.0.

**Table 4.6. Descriptive Summary of UGR Coding**

Code	Proportion of Tweets
Not Relevant	0.6097
Black People	0.1461
Black Women	0.0402
Black Men	0.0415
Empowering	0.0110
Racist	0.0384
Anti-Racist	0.0075
Positive	0.0216
Negative	0.0570
Neutral	0.0168
Racial Language or Slurs	0.0455
Generalizations or Stereotypes	0.0473
Political	0.0270
Hyper-sexualization	0.0132
Ignorant or Bad Humor	0.0150
Ambiguous	0.0415
Racial Comparison	0.0155
Cultural Appropriation	0.0013

N = 2265

**Table 4.7. Co-Occurrence of Select Codes in UGR Dataset**

	Black People	Black Women	Black Men	Racist	Anti-Racist	Empowering	Positive	Neutral	Negative
Black People	<b>331</b>	9	18	41	9	14	23	22	66
Black Women	9	<b>91</b>	0	8	0	5	12	5	22
Black Men	18	0	<b>94</b>	7	1	1	12	3	15
Racist	41	8	7	<b>87</b>	0	0	0	0	53
Anti-Racist	9	0	1	0	<b>17</b>	2	1	2	3
Empowering	14	5	1	0	2	<b>25</b>	12	1	1
Positive	23	12	12	0	1	12	<b>49</b>	0	0
Neutral	22	5	3	0	2	1	0	<b>38</b>	0
Negative	66	22	15	53	3	1	0	0	<b>129</b>
Racial Language or Slurs	30	1	2	31	0	0	0	0	32
Generalizations or Stereotypes	50	29	11	20	4	0	1	6	30
Political	23	1	7	3	1	5	4	2	8
Hyper-sexualization	7	5	7	1	0	0	2	0	3
Ignorant or Bad Humor	12	6	5	9	0	0	0	5	10
Ambiguous	19	4	6	3	0	0	1	6	1

Racial Comparison	14	2	1	2	3	2	1	3	4
Cultural Appropriation	3	0	0	1	0	0	0	0	0

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*Note:* Sample sizes shown in bold for select codes

## Chapter 5. Conclusion

Recently, health scholars have called for greater theoretical attention to the ways in which racism manifests culturally and produces structural inequalities, differential exposures to psychosocial stressors, and social environments that may harm the health of black mothers and their children. In addition, researchers have begun to investigate the utility of novel data sources such as Twitter, Google Trends, and digital trace data to proxy political and social climates. This dissertation acknowledges these disciplinary shifts and seeks to contribute to the body of research on racial disparities in low birth weight by assessing the influence of structural and cultural manifestations of racism. In this concluding chapter, I provide a brief review of the main findings of each empirical chapter, a summary of study limitations, and implications for future research based on the results presented in this dissertation as well as broader gaps in the literature.

### 5.1 Main Findings

The analyses that make up this dissertation were designed to flow together cohesively and build upon one another. The first empirical chapter (Chapter 2) builds the groundwork for the following chapters and investigates the relationship between structural manifestations of racial inequalities in power, prestige, beneficial social connections, and freedom and racial disparities in LBW. I find that measures of power and prestige, particularly when reduced to a single factor, have a robust association with the outcomes. That is, as the socioeconomic standing of black residents relative to whites improves, so does the relative health of black infants compared to white infants. However, the association between the outcomes and measures of beneficial social connections and freedom are less clear cut. Exploratory factor analysis suggests that measures used to capture these concepts are realizations of the same underlying construct. However, reducing these measures to a single index obscures the potentially protective

effects of racial residential clustering, particularly in regard to the black LBW rate. It is also worth noting that these concepts are inherently complex and the relationships between these concepts and health outcomes, particularly at higher levels of spatial aggregation, have yet to be fully articulated. This difficulty in measurement may partially explain the lack of association or counterintuitive associations between power, prestige, beneficial social connections, freedom, and LBW. In the following sections, I elaborate on the limitations of using these concepts in analysis and possible areas for future research that may elucidate how these concepts manifest at various levels of social organization and influence the health of populations.

Chapter 3 sought to investigate a possible source of this unexplained variance in the fully adjusted models from Chapter 2 in the form of “racialized social climates”, or places that put black residents at a greater risk of exposures to racial discrimination in various forms across various settings. In this chapter, I draw on analytic strategies by Caldwell (1986) and Kuhn (2010), in which both researchers identify countries that have exceptionally high or low rates of mortality despite having relative low or high levels of economic standing, respectively. Following this approach and using the fully adjusted models in Chapter 2, I identify 19 MSAs that are “exceptional” in regards to one or both outcomes. While each MSA stands out in regards to one or two of the predictors in the models, they by no means stand out in regards to all predictors. This further implies that there are other social conditions or other factors in general, contributing to the relative under- or over-achievement of these 19 MSAs.

Chapter 4 draws on recent analyses that have used proxy measures of racialized social climates and measures the sentiment of tweets about black people from each exceptional MSA. Based on a computer algorithm developed by myself and several collaborators, I identified 33760 tweets across the 19 MSAs as “about black people” and of those, 3757 were identified as

positive, 22060 as neutral, and 7943 as negative. However, it is not necessarily the case that MSAs with lower levels of each LBW outcome have fewer negative tweets about black people and more positive tweets about black people than MSAs with higher levels of each outcome. In addition, a comparison of human and computer generated annotations for a subsample of 2265 tweets suggest that the computer algorithm regularly misclassified tweets as about black people when they were in fact not relevant to the scope of this research project. Lastly, thematic analysis revealed that negative tweets about black people are more common than positive tweets, and that negative messages about black women differed in kind from negative messages about black men, imply that racialized language on Twitter is gendered as well.

## 5.2 Limitations

There are several limitations of this study worth noting. First, while more of a methodological decision than a limitation, the natality data and sociodemographic characteristics for the analyses in Chapters 2 and 3 were all measured at the MSA level. The decision to not include individual level data in this analysis was based on the overall goal of this project, which was to analyze area-based measures of racial inequality. In addition, individual-level natality data do not include many of the sociodemographic characteristics that may be potentially correlated with MSA-level characteristics. That is, while the natality data include robust measurements of infant health, pregnancy complications and maternal morbidities, and prenatal care, data on the social class, geographic mobility, and lived experiences of mothers and fathers is relatively sparse. In addition, many states do not reliably report maternal characteristics leading to non-random sample attrition. In contrast, data sets such as the Panel Study of Income Dynamics (PSID), would contain robust measures of socioeconomic status for numerous family members, residential mobility history, and comprehensive health histories as well. However,

compared to birth records data, data sets such as the PSID are limited in regard to the outcome, as far fewer PSID respondents have experienced a birth and among those who have, LBW is likely a rare event. As such, the decision to use the natality data for this analysis was based in a preference to increase the sample size for the outcome. In the absence of more complete data profiles for mothers, including individual-level data may have obscured the association between MSA-level characteristics and the outcome, when the association is actually due to maternal characteristics. That said, given the established association between certain maternal risk factors, such as smoking, education, and marital status, and LBW, the analyses presented here may be limited in their interpretation. Including maternal characteristics in a multilevel model, as is common in epidemiological research on infant health outcomes, would be an immediate next step for the analysis.

Another limitation is the absence of other measures at the MSA-level that may influence the likelihood of LBW. Data on the level of social disorganization (i.e., violent crime), health and social services (i.e., number of hospitals), and nutritional services (i.e., presence of food deserts), within an MSA would have all been likely candidates for inclusion in regression analyses. In addition, some of these measures as well as others not listed here may more accurately capture aspects of power, prestige, beneficial social connections, and freedom than the measures included in this analysis. While the black-white gaps in occupational attainment, educational attainment, income, unemployment, and poverty seem to capture the underlying concepts of power and prestige, the same doesn't appear to be true for the measures of beneficial social connections and unfreedom. While I refer to the factor loading for these variables as "spatial disadvantage", it may be more appropriate to refer to this factor as "unfreedom", as poverty and racial isolation certainly reflect interpersonal and institutional processes that restrict

where people are able to live. This would suggest that the measures racial and poverty isolation do not reflect access to beneficial social connections at the MSA-level. In addition, other variables not included here may further identify the circumstances in which these mechanisms matter more or less for health outcomes, such as areas where isolation has been present for longer periods of time compared to areas that are newly isolated.

For the analyses that use data from Twitter, there are several limitations that may have influenced results. First, as noted in Chapter 4, the computer algorithm regularly identified codes that were not actually about black people. As a result, the true number of tweets about black people in the dataset is unknown. It is likely that fewer than 33760 tweets across the 19 MSAs identified as exceptional were actually about black people, given that many tweets analyzed by UGRs included the word “black” but were not about black people. Likewise, there was considerable disagreement about the sentiment of tweets between computer and UGRs annotations. This implies that both the computer algorithm as well as human coders require further training. UGRs also reported a high degree of coder fatigue due to the number of codes provided. As such, it may be the case that UGRs underreported the true prevalence of certain codes. An additional limitation noted by UGRs was their lack of knowledge of certain topics as well as their positionality. While these shortcomings were described in detail in Chapter 4, it is worth noting that in the larger project from which the computer algorithm used here was developed, my collaborators and I also found differences in coding results for MTurkers who identified as non-white compared to MTurkers who identified as white. As such, results for coding analyses may be biased by codes from white UGRs.

### 5.3 Implications for Future Research

The main findings and limitations suggest several opportunities for future research. As noted above, an immediate next step for the analyses in Chapter 2 would be to integrate individual level data and analyze the associations between MSA-level measures of racial inequality, individual-level maternal characteristics, and LBW using multilevel models. In addition, integrating other sources of data on crime, access to health care, pollution, and other environmental characteristics would reduce omitted variable bias. Substantively, the findings in Chapter 2 suggest a need to further investigate the micro-level processes that occur in racially clustered communities. Research by Bell (2006) argues that racially clustered communities may have strong social support networks and that the social environments in these communities mitigate the negative consequences of residential segregation on health. It would be worthwhile to determine what these conditions are for both policy and public health practice. In addition, as the literature review in Chapter 2 notes, there is relatively little research on the association between prestige and/or power and birth outcomes. As such, it is unclear exactly how or if social honor and control of others matters for health. Further articulation of how these processes influence health, particularly the health of people who may become pregnant, may provide practical insights for policies in school and workplace settings. For example, given the findings by Forman (2003) that observable racial inequalities within workplaces are detrimental to the health of black male workers, it may also be the case that black women experience similar inequalities in their work and that these observable injustices contribute to poor birth outcomes.

For the analyses presented in Chapter 3, an immediate next step would be to provide more detailed “case studies” of each exceptional community. It may be the case that there are historical, geographic, or political aspects of these communities not reviewed here that influence

their under- or over-achievement in regards to LBW. For example, Ithaca, New York stands out as an MSA that has a higher rate of black LBW than expected, a larger black-white LBW gap than expected, and more negative tweets about black people. Ithaca is also home to Cornell University, an Ivy League school. However, the median household income in Ithaca is half the national average and black households in Ithaca earn 0.45 cents to the dollar that white households earn. That is, despite housing one of the most prestigious universities in the country, the residents of Ithaca do not seem to benefit economically from the presence of this institution. Further investigation into Ithaca and the other exceptional MSAs may reveal aspects of these communities that matter for maternal and infant health.

For the analyses presented in Chapter 4, a clear immediate next step is to refine the computer algorithm used to classify tweets as about black people as well as positive, negative, or neutral. It would also be worthwhile to incorporate aspects of the methodology used by Nguyen et al. (2018; 2019) to further refine the algorithm. In addition, it would be worthwhile to estimate the proportion of negative or positive messages about black people for the entirety of the DOLLY data set. This would provide the largest analysis of racialized language on Twitter to date, and the results could be used for various applications in social science and health research. An additional avenue for future research would be to integrate other forms of media data including data from newspapers, local bills and council meetings, and Facebook posts, among other sources. Lastly, I recommend that researchers hoping to use these data sources to measure racism think critically about the positionality of the people doing the coding. Computer algorithms can only learn what we tell them and results from MTurks and UGRs suggest that human coders from different racial groups may interpret text differently. Researchers should

seek to take the same approach of many interviewers and attempt to match coders based on race and other characteristics relevant to their research questions.

#### 5.4 Concluding Remarks

The results of this dissertation represent a first step in integrating structural measures of racial inequality and novel data sources that may capture cultural aspects of racism into a cohesive analysis. While research on the associations between racism and health has primarily relied on the stress paradigm as a theoretical orientation, scholars have continually urged health researchers to turn their attention upstream to the macro-level processes that put individuals and groups at “risk of risks”. As Hicken and colleagues (2018) note, there is a need to incorporate more structural and cultural manifestations of racism into analyses. This dissertation suggests that the associations between one form of structural inequality and health, at least at the aggregate, is robust: as the relative SES of black Americans improves the risk of LBW among black Americans reduces, in both an absolute and relative sense. However, associations between other measures of structural inequality, namely racial residential segregation and racial differences in jail admission, are not as straightforward. In addition, while social media and other forms of digital trace data may provide insights into the racialized beliefs of MSA residents, there is much refining necessary to achieve this. Regardless, the analyses presented here further support the sentiments expressed by Eichelberger et al. (2016): the gap in LBW between babies born to black and white mothers is the product of a broken *system*, not a broken group of women.

## VITA

Savannah Larimore graduated from North Carolina State University in 2012 with degrees in Sociology and Women & Gender Studies, in addition to a minor in Statistics. She attended the University of North Carolina at Charlotte where she earned an MA in Sociology. Her thesis, “Cultural Boundaries to Access in Farmers Markets Accepting SNAP”, was published in *Qualitative Sociology* in 2018. At the University of Washington, Savannah completed concentrations in Demography and Statistics, in addition to her doctorate in Sociology. She will begin work as a Post-doctoral Fellow at Washington University in St. Louis in the fall of 2019.