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Racial Differences in the Social Determinants of Infant Mortality: A County-Level Analysis

Anna Claire Church

RACIAL DIFFERENCES IN THE SOCIAL DETERMINANTS OF INFANT MORTALITY: A COUNTY-LEVEL ANALYSIS

by

Anna Claire Church

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ABSTRACT

Infant mortality rates (IMRs) are considered to be one of the most important indicators of a healthy society and a key marker of maternal and child health. In the United States, progress has been made in reducing the overall infant mortality rate, but this reduced aggregated rate masks significant racial disparities. The objective of this study is to systematically examine racial differences in a number of social determinants of infant mortality at the county-level, specifically differences between non-Hispanic Black and non-Hispanic White populations. Multivariate OLS regression modeling is used to analyze the association between the demographic, economic, and health predictor variables and IMRs. The results show that while there are marked differences in the predictors of Black and white IMRs, there are also remarkable similarities. Median household incomes and numbers of practicing midwives are found to be two of the significant factors in reducing infant mortality rates for both groups.

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INTRODUCTION

Infant mortality is considered an important indicator of a nation's health and well-being, as well as a common measure for ranking countries relative to one another. Despite the United States being one of the world's wealthiest nations, it does not fare well in comparison with other similarly developed nations regarding its infant mortality rate (IMR), ranking 26th out of 29 Organisation for Economic Co-operation and Development (OECD) countries in 2010 (MacDorman et al. 2014). This lower ranking is in large part due to the fact that the US has a higher level of income inequality than other Western nations, and high levels of income inequality within countries have been shown to predict worse population health (Hill 2016). These poor outcomes are particularly pronounced in the African American population, where an infant mortality rate of 2.2 times that of non-Hispanic whites is observed in 2016, a disparity that has persisted for decades (Murphy et al. 2017). A racial disparity of this magnitude reflects larger inequalities in population health status, which have proven resistant to intervention (Institute of Medicine 2002; Braveman et al. 2011; Arcaya, Arcaya, and Subramanian 2015). Speights et al. (2017) found that if the IMR for Blacks[1] was equal to that of whites over a 13-year period (1999-2013), 64,876 infant lives would have been saved, approximately 12 infants a day. These estimates are a staggering reminder of the tragedy of racial disparities in IMRs and draw attention to the incalculable pain and suffering which they cause.

[1] I have chosen to capitalize Black, but not white, throughout this paper. This decision was made with explicit attention to power and privilege. I capitalize Black because it represents a cultural group with a shared history of culture and community which goes beyond the label of 'Black' (Gotanda 1991; Crenshaw 1994). Lori Tharps (2014) said it best, "Black with a capital B refers to people of the African diaspora. Lowercase black is simply a color" (p. A25). On this same note, white remains in the lowercase, with the exception of when I refer to a specific label or categorization found in the data set. There, I defer to their capitalization. "White" is not a proper noun as it does not connote a specific cultural group with any shared heritage or history (Crenshaw 1994). Law scholar Neil Gotanda (1991) best explains this: "To the extent that Black "summarizes" relations of racial subordination, white "summarizes" racial domination. As a term describing racial domination, "white" is better left in the lower case, rather than privileged with a capital letter. "Black" on the other hand, has deep political and social meaning as a liberating term, and, therefore, deserves capitalization" (p. 4). When the label 'African American' is used, it is in direct reference to a statistic which used that racial categorization, and I remain true to the original terminology.

Infant mortality has been extensively studied by social scientists, particularly medical sociologists and public health researchers, for decades. Link and Phelan (1995) first argued that too much attention has been devoted to identifying individual risk factors that affect health and proximal causes of disease such as diet, smoking, and exercise, and far too little to understanding how social conditions affect health and health behaviors. This sentiment is reflected by Montez, Zajacova, and Hayward (2016) as they emphasize the influence of socioeconomic and political contexts in reducing women's mortality rates, over and above the role of individual personal choices and characteristics. This project continues in this tradition of macro-, societal-level conditions as explanatory mechanisms for the persistent racial differences in IMRs, while considering the structure of the society into which women are born, live, and grow. Most of the infant mortality research that has *not* been focused on the individual has been done at the state-level, which can mask intra-state variation. A better understanding of what factors predict infant mortality is needed to guide future interventions that may potentially reduce these disparities.

This paper is one of the first, to my knowledge, to examine the association between county-level demographic, economic, and health measures and infant mortality and if they *differentially* predict infant mortality for Black and white populations. Most prior work on the subject mentions race or racism, at the very least in a cursory manner, but few, with the important exception of Wallace et al. (2017), use structural or systemic racism theory as explanatory mechanisms for their results. My research questions are: (1) Do social determinants of infant mortality differ by race? (2) How can structural and/or systemic racism theory offer explanatory perspectives for the differential association of social determinants by race?

LITERATURE REVIEW

Infant mortality is a fundamental measure of health and well-being that has been studied substantially in the academic literature. The foundation of infant mortality research is the descriptive body of work, which has highlighted overall trends and disparities, and laid the groundwork for increased attention to the social determinants of IMRs. This includes describing recent declines in IMRs (MacDorman, Hoyert, and Matthews 2013) and providing an overview of trends and patterns in fetal mortality, preterm birth, and infant mortality (MacDorman 2011). The findings highlight the overall declines of race-specific IMRs over the past ten years, while drawing attention to the enduring disparity between racial/ethnic groups. It has also been observed that IMRs vary by place and that disparities exist based on regional location (MacDorman et al. 2013). This is key for framing questions about how place affects health, but both works examine trends at the state-level leaving unanswered questions about the relationship between place and infant mortality at the county-level.

Speights et al. (2017) sought to determine if individual state-level infant mortality trends from 1999 to 2013 between Blacks and whites were converging (i.e., growing closer together) or diverging (i.e., growing farther apart) and to estimate how long it would take for racial disparities in state IMRs to be eliminated at their current rate of change. They found that all states had improved their Black IMR to varying degrees and predicted that Massachusetts would be the earliest state to reach racial equality in IMRs by 2025, although at the current rate of change, many states will never achieve elimination of these racial disparities. Future research has been called for that will "explore differences in social determinants, policies, and health systems characteristics that might help understand these causes and correlations" between different risk factors of infant mortality (Speights et al. 2017:776). I address this gap in the literature by producing a more complex, nuanced picture of the social determinants of race-specific IMRs.

Other studies have conducted bivariate analyses to examine links between infant mortality and one specific predictor variable. While this type of work cannot provide a broad-based picture of the myriad causes and determinants of infant mortality, it can provide an indepth look at a significant or understudied relationship. Some examples are the link between gestational weight gain (GWG) and infant mortality (Davis, Hofferth, and Shenassa 2014) and how minimum wage policies affect IMRs at the state-level (Komro et al. 2016). Interestingly, across all models, a dollar increase in the minimum wage above the federal level was associated with a one to two percent decrease in LBW births and a four percent decrease in postneonatal mortality (28-364 days old) (Komro et al. 2016). This adds fuel to the argument that macro-level conditions and policies affect health outcomes in real and tangible ways outside of individual human behavior.

Another component of this body of work is the assessment of the differential contribution of socioeconomic position and maternal characteristics, such as number of prenatal visits, parity, and education level, to black-white disparities in infant mortality across specific causes of death in the state of Michigan (El-Sayed et al. 2015). The authors used a similar methodology as use for this study, but they utilized individual-level data as predictors rather than social-structural measures. This is particularly important when considering racial disparities because by focusing on behaviors and predictors specific to the mother, authors may insinuate, even if unintentionally, that there are inherent differences in Black and white women and perpetuate the narrative of Black women as embodying inherently risky bodies when it comes to pregnancy. The individualization of risk often leads to the individualization of blame (Waggoner 2017), and while there indeed may be behavioral or other individual differences across varying categorizations of mothers, these differences are the product of broader social forces that influence and constrain behavior and decision making.

The Importance of Race

With racial differences in infant mortality being the focus of this study, it is critical to emphasize the sociological interpretation of race. That is, race is a socially constructed category which has had varying definitions and hierarchical systems throughout history. It is also important to remember that while race is a social construct (i.e., not real) its consequences on individual lives in social, political, and health realms are quite real. Social constructionist frameworks theorize racial groups as socially created through the process of assigning meaning to real, perceived, or ascribed differences between groups and consequently using those differences as the basis for distributing power (Bonilla-Silva 1999; Hill 2016). The dominant medical paradigm of the late 19th and early 20th century was that any racial differences in health were due to innate biological differences between members of those groups (Williams and Sternthal 2010). W.E.B. Du Bois (1899) was the first scholar to push back against this narrative by drawing attention to the differences in social conditions in which Blacks and whites lived and by theorizing these racial differences in health as an indicator of racial inequality in the US.

The disproportionate burden of infant mortality in the African American population is significant. In 2015, the white IMR in the US was five per 1000 live births, while the Black IMR was 11.2 per 1000 live births, approximately 2.2 times higher than whites (Smith et al. 2018). Infant mortality rates for college-educated African Americans are more than twice as high as similarly educated white and Hispanic women, and Black female college graduates have higher rates of infant mortality than Hispanic and white women who have not even finished high school (Williams 2013). These incredibly stark statistics make it difficult to argue that the social construction of race is not a defining factor in the continuing struggle of racial disparities in IMRs. It has been illustrated time and time again that sociodemographic and proximate factors including rates of LBW and premature births are not able to completely explain racial mortality differentials (Hummer 1993). One theory posits that the above disparities are in part due to the fact that Black women experience greater lifetime exposure to acute and chronic stressors, which include racism, and this increases their susceptibility to preterm delivery among other pregnancy health complications (Geronimus 1992). Black women may age prematurely because of this increased exposure to traumatic life events beginning from early childhood, referred to as "stress age", or "weathering" (Geronimus 1992; Hogue and Bremmer 2005). This phenomenon has been examined further in the work of Buescher and Mittal (2010) and Hauck, Tanabe, and Moon (2011), providing more recent evidence to support the hypothesis that systemic racism, or chronic exposure to stressors related to poverty and racism, influence health outcomes for women and infants. And while this process occurs at the level of the individual, the cause of it is not. Hill (2016) describes the United States as a "racialized society" meaning that race is embedded in the national consciousness. A structural interpretation of race, namely a theory of racism based on the notion of racialized social systems, has been a newer way to approach the study of racial phenomena (Bonilla-Silva 1997). Hill's (2016:4) major argument is that African Americans live in this pervasively racialized society where "blackness signifies racial inferiority and leads to policies, attitudes, and stereotypes that adversely affect every aspect of black life, fostering sickness and early death." When health researchers ignore the "racialized society", the interpretation of data and results is less meaningful, and the bigger picture is lost.

Wallace et al. (2017) took a significant step toward accounting for the "racialized society" in their work. They explored how state-level racial inequities in social conditions were associated with state-level racial inequities in infant mortality. This is one of the few studies which utilizes a national sample to analyze how social predictors may differentially impact Black and white IMRs. They found that inequities in employment, prison incarceration rates, and median household income were significantly associated with worse Black IMRs but were not associated with white IMRs in a negative or positive way. This emphasizes the need for more granular studies of these phenomena as there can be high amounts of intra-state variation (Wallace et al. 2017). This was also one of the only works, to my knowledge, which attempts to link incarceration rates to IMRs. There is a large body of work which has linked incarceration to health in general, particularly the health of those imprisoned persons themselves (see Massoglia and Pridemore 2015 for a thorough review). While it is clear that mass incarceration has had deleterious effects on the health and economic well-being of broader communities (Tyler and Brockmann 2017; Cox 2018), little is known about how it might be related to disparities in IMRs.

County-Level Infant Mortality Research

The previously discussed infant mortality findings use the state as the unit of analysis, but to a lesser degree the literature contains sub-state findings, which uncover trends that may be masked in state level work. I will begin with pieces which highlight significant associations in smaller geographic areas, which are an important foundation for this study. One of the first studies to examine the relationships between infant mortality and women's health and behavior was conducted on individual-level data in one single county in Tennessee (Scott-Wright, Wrona, and Flanagan 1998). Singh, Kogan, and Slifkin (2017) compared disparities in infant mortality between Appalachia and the rest of the country, aggregated to the county-level, and found significant differences in causes of infant death, specifically deaths due to birth defects and SIDS, due to Appalachia's status as a generally economically depressed region with distinct cultural characteristics. The authors acknowledged that their study did not quantify the independent impacts of socioeconomic conditions on these differences in IMRs, which is critical in explaining *why* differences exist not just highlighting their existence in a general sense (Singh, Kogan, & Slifkin 2017). Continuing with this focus on unique regions in the US, Eudy (2009) explored disparities in IMRs within the Delta region at the county-level and found that the effects of regional differences lessened over the study period (late 1970s, late 1980s, and late1990s) but the effects of poverty and racial composition continued to have strong effects on

IMRs. However, her work did not examine disparities in IMRs by race because of data limitations in rural counties, and I build upon this work by incorporating racial differences in social determinants of IMRs in the current research.

In addition, there have been systematic nationwide studies conducted which have focused on the relationships between IMRs and other social conditions at the county level, including the associations between county-level measures of infant mortality and US state-only funding for family planning and abortion (Krieger et al. 2016). They concluded that decreased public state funding for abortion in the US was associated with an increased risk in county-level infant death (Krieger et al. 2016). Hollar (2016) used a powerful methodology, which I draw from, in order to determine what county-level factors, including health, socioeconomic, and demographic/social, affected infant and child health outcomes. He found significant regional patterns or spatial correlations for these negative outcomes, but he did not separate the IMRs by race in order to determine any differential association.

It is difficult to obtain IMRs for many counties within the US due to small population numbers and lack of available and reliable data (Rossen, Khan, and Schoendorf 2017). Some have attempted to overcome this limitation by proposing a geographic modeling method in which to estimate IMRs for smaller counties where data is not available and to model geographic variation in IMRs across the country (Rossen et al. 2017). The authors described the geographic variation in IMRs that they observed but did not attempt to explain any potential reasonings for *why* there was geographic variation in IMRs. Bekemeier et al. (2014) used detailed data of local health jurisdictions or departments (LHDs) in the states of Florida and Washington to examine any impacts of maternal child health (MCH) spending by LHDs on birth outcomes. They found that increased MCH spending by LHDs did improve birth outcomes for the counties they examined. Orchard and Price (2017) used LBW and preterm birth as outcome measures, rather than infant mortality, but the three outcomes are closely correlated. They examined whether the Black-white gap in adverse birth outcomes was larger in counties with higher levels of racial prejudice. This is important work because evidence has indicated that racial prejudice can influence a woman's access to quality health care and can act as a psychological stressor in the woman's life (Rich-Edwards et al. 2001; Mustillo et al. 2004; National Research Council 2004) which, as discussed previously, can prove devastating for the health of both the woman and fetus. Incredibly, but not surprisingly, the Black-white gap in LBW is 14 percent larger in counties with high racial prejudice as compared to those counties with low measures of prejudice, and the Black-white gap in preterm births is 29 percent larger in high prejudice counties (Orchard and Price 2017). Due to this finding, I also included in my models one of the measures of prejudice that Orchard and Price (2017) utilized which has been understudied in relation to infant death. Further explanation of this measure is to follow.

Racial disparities in IMRs have been repeatedly illustrated in recent studies, as well as the dire consequences that this difference in deaths has for families, communities, and the entire US. It is critical to move away from individual-level measures and toward a holistic picture of the environment in which women live and give birth. There is some current research moving in this direction, but there is still a great deal that is not known about how societal- and structural-level factors influence IMRs. There is even less known about how these factors may be differentially associated with IMRs by race, or, in other words, if Black and white IMRs may be influenced by or associated with different things. When measuring how social determinants are associated with a population-level indicator of infant mortality, one which combines Black and white IMRs as a single rate, these associations are largely dictated by the white population estimates given their usual larger size relative to black populations at the state- and county-level (Wallace et al. 2017). This means that very little is known about what structural, health, or economic measures may be associated with Black IMRs specifically and to this point, most of what is known about population patterns of association with IMRs is mirrored within white-specific IMRs.

My work attempts to bridge many of the major gaps in the current infant mortality literature by analyzing social predictors of *race-specific* IMRs at the county-level unit of analysis. This project focuses on IMRs and their associations for counties with populations of 250,000 persons or more, and these largely populated areas allow an analysis of race-specific IMRs and their associations with various factors. There is a dearth of studies on infant mortality which either tackle race as a social construction in a meaningful way or interpret their results through the lens of a racialized society and what that means for the lives of those in the sample. This project is a critical contribution to the current literature and will advance the conversation on racial disparities in IMRs in important ways.

METHODS

Infant mortality rates were obtained from the Centers for Disease Control and Prevention (CDC) WONDER Online Database, specifically the Linked Birth/Infant Death Records 2007-2015, ICD 10 Codes file.[1] These data are the gold standard for the accurate measurement of IMRs by race (MacDorman et al. 2013; Krieger et al. 2016; Speights et al. 2017; Wallace et al. 2017), because it links an infant's death record with its birth certificate ensuring a more accurate measurement of race/ethnicity than IMRs obtained from the CDC Compressed Mortality File (CMF). The CMF measures for race/ethnicity are based exclusively on death records, where race is known to be less accurately reported than on birth certificates (Office of Public Health and Science 2015). This is particularly important when grouping the data by race as overall

[1] United Department of Health and Human Services (US DHHS), Centers of Disease Control and Prevention (CDC), National Center for Health Statistics (NCHS), Division of Vital Statistics (DVS). Linked Birth/Infant Death Records 2007-2015, as compiled from data provided by the 57 vital statistics jurisdictions through the Vital Statistics Cooperative Program, on CDC WONDER On-line Database.

trends between the two are unlikely to differ but in more nuanced statistical analyses, such as this study, any differences in the measuring of race could be critical (MacDorman et al. 2013). I chose to aggregate the data to the county level in order to capture trends that would most reflect the day-to-day environment and structural conditions and constraints in which these women lived and in which these infant deaths occurred. As mentioned, much infant mortality research has been done at the state-level, which can mask intra-state variation in physical environment and resident health. The county is the primary legal division of most states and many of them are functioning governmental units themselves. Also, county health departments are primarily responsible for health initiatives and interventions which would directly impact IMRs and could be informed by studies such as this.

The linked birth/infant death records only provide county-level data for those counties with a population of 250,000 persons or more, which means that this study is an analysis of social determinants of infant mortality in urban America. While this, of course, limits those counties which can be included in the analysis, these larger counties account for a growing proportion of the US population. It is thought by demographers that within twenty years almost half of the U.S. population will live in just eight states and approximately 200 counties (Bump 2018). The concept of homogenization of urban landscapes proposes that most urban centers are beginning to look alike, meaning that they have very similar structures and environments that citizens are living in regardless of their geographic location (Groffman et al. 2014), allowing for reasonable direct comparisons of these highly populated counties. There is a lack of nationwide data for IMRs across the country, especially at more granular levels such as county- or even neighborhood-level rates (Bekemeier et al. 2014). This issue is particularly heightened when attempting to look at these rates differentially by race as large populations are required.

The IMRs used for this paper were measured as a five-year sum (2011-2015), which is often done to increase statistical power of the measure, to provide a larger number of cases with which to work with, and to smooth out high and low spikes in the data that may occur in a single year (Scott-Wright et al. 1998; Eudy 2009; Speights et al. 2017; Wallace et al. 2017). Working with a sum of multiple years is also a method of attaining valid and reliable numbers, as infant deaths are an outcome of low incidence. There are 72,359 total deaths and 13,028,290 total births in the original data set and this number was reduced to 32,798 deaths and 5,765,475 births after eliminating counties which did not have both a Black and a white IMR, which was required to be able to determine differential association of the social determinants, and those which had unreliable rates. The final data set had 160 counties, the unit of analysis, which were distributed through 37 states.[2]

The county-level measurements of demographic, economic, and health variables, with the exception of the dissimilarity index and the implicit prejudice measure, came from the Area Health Resource File (AHRF) 2016. The AHRF requires that the data provided by counties be accurate, or at least generally accurate if no better data exist, and this data set is generally accepted as a valid source of measurement.[3] The dissimilarity index was obtained from the American Communities Project, and the indices were originally matched with the geographic identifiers of the respective metropolitan statistical area (MSA).[4] The MSAs were linked with their respective Federal Information Processing Standard (FIPS) codes, unique county identifiers,

[2] States included in the data set are: AL, GA, FL, SC, NC, TN, KY, VA, MD, DE, NJ, PA, NY, MA, RI, CT, OH, IN, IL, MO, AR, LA, MI, WI, IA, MN, NE, KS, OK, TX, CO, AZ, NV, CA, OR, WA, D.C. States which are not included in the data set are: ID, MT, WY, ND, SD, NM, MS, WV, VT, NH, ME, AK, HI, UT.

[3] *Area Health Resources Files (AHRF) 2015-2016.* US Department of Health and Human Services, Health Resources and Services Administration, Bureau of Health Workforce, Rockville, MD.

[4] American Communities Project, Brown University. "Diversity and Disparities." Retrieved from https://s4.ad.brown.edu/projects/diversity/Data/data.htm.

by merging the two separate data sets. The geographic area of an MSA does not always line up exactly with the geographic area of a county as an MSA usually consists of a core urban area with a large population and its surrounding region, which may include several adjacent counties (Office of Management and Budget 2000). Therefore, the MSA-county match is not perfectly precise, but is a well-established methodological approach to study urban area relationships (US Census Bureau 2010). The implicit prejudice measure was obtained from the Project Implicit website, and data was collected by Xu, Nosek, and Greenwald (2014) for the year of 2010. The approximately 225,000 individual Implicit Association Test (IAT) scores were aggregated to county-level average IAT scores and matched to the 160 counties in the original data set.

Measures

The outcome or dependent variable is the county IMRs for non-Hispanic White and non-Hispanic Black infants for 160 urban counties with a population of at least 250,000. Infant mortality rates are measured as the number of infant deaths prior to their first birthday per 1,000 live births. Because the linked birth/infant death files only include measurements for counties with a quarter million population, there is some year-to-year fluctuation in counties which are eligible for inclusion as populations change over time. There are also IMRs which are suppressed by the CDC for confidentiality purposes (i.e., when the number of deaths is less than ten), and also values which are unreliable (i.e., when the number of deaths is less than twenty). The IMRs were grouped by race and county, restricted to non-Hispanic White and non-Hispanic Black infants, singleton births, and for the years of 2011 to 2015. This focus on white and Black IMRs (excluding Hispanic ethnicity) is a very common approach to the study of infant mortality, as it is difficult to get large enough numbers of deaths for other race/ethnic groups and be able to conduct comprehensive analyses (Rossen et al. 2017).

The independent or predictor variables that follow are grouped by their respective analytic models and are each measured at the county level: [demographic: percent Black/African American, dissimilarity index, Implicit Association Test score, percent imprisoned, and unemployment rate of those 16 years aged and above]; [socioeconomic: percent persons 25+ years with 4+ years of college, percent under 65 years of age that are without health insurance, percent of families with a female head of household, median household income in the tens of thousands of dollars, percent persons aged 0-17 in poverty, percent persons age 18 and over in poverty, and percent of households receiving Food Stamp/SNAP]; [health: number of registered midwives, low birth weight (LBW) births, very low birth weight (VLBW) births, preterm births, teen birth rate, and number of births to unmarried women]. Due to high levels of multicollinearity between some of these measures, multiple models are sometimes used to examine the relationships within a single category.

The independent variables chosen are the usual suspects in infant mortality research, with the addition of the dissimilarity index, the Implicit Association Test score, and the midwife variable. The dissimilarity index (D) measures whether one particular group is distributed across census tracts in a metropolitan area in the same manner as another group and is considered a measure of segregation (American Communities Project 2010). Values for D range from 0 to 100. The higher the number, the more people that must move for the numbers to be even and the more segregated the area (McFarland and Smith 2011). For example, a dissimilarity index of 60 is considered to be quite high and would mean that 60% of the members of one group would need to move to a different tract in order for the two groups to be equally distributed across the census tracts. Values of 40 or 50 are considered a moderate level of segregation, and values of 30 or below are considered to be fairly low. Increased levels of segregation have been shown to lead to concentrated poverty (Massey and Fischer 2000), which then leads to a withdrawal of resources from that area (Massey and Denton 1993). Regarding the effects on health, it was illustrated through the examination of the relationship between segregation and LBW and IMRs in MSAs that segregation had a positive relationship with low birth weight and infant mortality among Black individuals, meaning that the more segregated (i.e., the higher the dissimilarity index), the higher the rates of LBW and infant mortality were (McFarland and Smith 2011). A gap in the current literature on the relationships between infant mortality and segregation is the use of race-specific models (McFarland and Smith 2011), which this study is predicated on, and I attempt to further examine the relationships between segregation and white and Black IMRs.

Implicit prejudice is measured by the overall score on the Implicit Association Test (IAT), which is a task designed to tap into automatic associations between concepts such as Black people or gay people and evaluations (i.e., good, bad) or stereotypes (i.e., athletic, clumsy) associated with the concepts (Project Implicit 2011). This test is an important tool for measuring prejudice, as it reduces potential biases in self-reported measures of prejudice, which are susceptible to a lack of awareness of any held biases, or social desirability bias as it is often socially sanctioned to openly admit racial prejudice (Greenwald, McGhee, and Schwartz 1998). It has been used to study how measures of implicit (and explicit) prejudice affect birth outcomes (Orchard and Price 2017), the effects of gender stereotypes on nation-level sex differences in 8^{th} grade science and mathematics achievement (Nosek et al. 2009), and implicit racial and weight bias among physicians and the effects on quality of care (Sabin, Rivara, and Greenwald 2008; Sabin, Marini, and Nosek 2012) as a few examples.

The IAT asks participants to match positive and negative words, as well as images of African Americans and European Americans into categories in two different sorting conditions. In one condition, respondents match positive words and pictures of European Americans using one response key and negative words and pictures of African Americans using another response key. In the other condition, the pairing is reversed with positive words associated with pictures of African Americans and negative words with those of European Americans. The order of the conditions presented to the respondent is randomly assigned. The test measures the time elapsed, or latency, between the respondent assigning a certain face to a category and then a positive or negative word to that same category. Those with more prejudiced tendencies toward African Americans will be slower to assign a positive word to that category (Greenwald et al. 1998). The scoring system for the IAT results range between -2 (extreme preference for African Americans) and 2 (extreme preference for European Americans). I hypothesize that the higher the implicit prejudice measure (i.e., the higher the preference for European Americans) the higher the infant mortality rates for Black infants will be. I expect either the implicit prejudice measure to have a negative relationship with white IMRs (i.e., the higher the preference for European Americans, the lower the white IMRs) or to have no significant relationship with white IMRs.

Regarding the midwife variable, the number of registered midwives is obtained from the Centers from Medicare and Medicaid Services (CMS) National Provider Identification (NPI) File. These include certified nurse-midwives (CNMs) and certified midwives (CMs), which are essentially the same in terms of clinical skills and required certification exam but differ by credentials. CNMs are required to hold a registered nursing license. Midwives have been associated with an increase in optimal maternal and infant childbirth outcomes, but few empirical analyses of this association exist. The practice of midwifery is within the regulatory power of individual states, therefore, laws concerning it are fragmented and vary dramatically from state to state (Yang and Kozhimannil 2015). A groundbreaking study by Vedam et al. (2018) created a Midwifery Integration Scoring System (MISS) to give scores for each state with a maximum value of 100 (i.e. midwifery most integrated) and found that states which had midwifery practice more fully integrated into their health care systems with less restrictions had some of the best maternal/infant outcomes as compared to states which had the most restrictive midwife laws and practices which tended to have significantly worse outcomes.

Vedam et al.'s (2018) work was one of the first to empirically link integrated midwifery care and health outcomes in this manner, while also raising the possibility that greater use of midwives could reduce racial disparities in pregnancy care. The integration of midwifery care is also significantly associated with the actual number of practicing midwifes, as those states with less restrictions tend to have twice as many practicing midwifes as those with stricter regulations (Yang, Attanasio, and Kozhimannil 2016). This is important to note as the variable used for this study only measures the actual number of practicing midwifes, not the integration of midwifery practice, but this integration, or lack thereof, is likely to influence the variable and perhaps its association with IMRs. The states in my sample included the lowest MISS score (NC) to the highest (WA) with the average score being 36, equaling the average for the national sample.[5] I hope to build on the previous work by determining how the number of registered midwives may (or may not) be associated with non-Hispanic Black and/or non-Hispanic White IMRs and move the path forward on this issue.

Analytic Strategy

The analyses to follow will summarize the dependent and independent variables using descriptive statistics. I will then employ ordinary least squares (OLS) regression analysis separately for white IMRs and Black IMRs in order to compare significant associations and unstandardized coefficients using the Clogg statistic between IVs and race-specific DV. All statistical procedures are run using the statistical software SPSS, Version 25. Linear regression is

[5] The Midwife Integration Scoring System (MISS) values for each state in the sample in ascending order are as follows: NC: 17, AL: 18, OH: 20, KS: 22, NE: 23, OK: 24, IL: 25, IA: 25, KY:25, PA: 26, LA: 28, CT: 28, DC: 29, NV: 29, GA: 30, MA: 31, AR: 32, MI: 34, SC: 34, IN: 36, MD:39, MO: 41, TN: 41, VA: 41, CO: 41, FL: 42, DE: 42, TX: 43, WI: 43, CA: 46, MN: 50, AZ: 52, RI: 53, NY: 54, NJ: 55, OR: 58, WA: 61. These values were obtained from Vedam et al. (2018).

an oft used methodology for infant mortality research in particular and health disparity research in general as it treats one variable, or many variables, as explanatory and one as a dependent variable and measures how one is associated with the other (Eudy 2009; Goyal et al. 2017; Speights et al. 2017). The predictor variables will be divided into three models for both Black and white IMRs for a total of six models: (1) demographic (e.g. percent Black/African American, dissimilarity index, IAT score, unemployment rate, & percent imprisoned); (2) socioeconomic (e.g. percent without health insurance, median household income in tens of thousands of dollars, adult and child poverty, percent female head of household, percent of households receiving Food Stamps/SNAP, & college education); (3) health (e.g. LBW, VLBW, midwives, preterm birth, teen birth rate, & births to unmarried mothers). A fourth model, the full model, will also be analyzed with a mixture of predictor variables for both groups from the previous three models. An example of the division of the models is displayed below in Table 1. The models and the number of the variables contained therein are drawn from Hollar (2016), who performed a regression of similar variables onto county-level IMRs but lacked race-specific models.

Table 1. OLS Regression Model Division

Independent Variables	Model 1	Model 2	Model 3	Model 4
Percent African American	X	------------	-----------	X
Dissimilarity Index (D)	X	------------	-----------	X
IAT Score	X			X
Percent Imprisoned	X	------------	-----------	X
Unemployment Rate	X	------------	-----------	X
Percent College Educated	---------	X	-----------	X
Percent Uninsured	----------	X	-----------	X
Percent Female Head	----------	X	------------	X
Median Household Income	----------	X	------------	X
Percent Food Stamp/SNAP	----------	X	------------	X
Percent Child Poverty	----------	X	------------	X
Percent Poverty	----------	X	------------	X
Midwives	----------	-----------	X	X
Low Birth Weight Births	----------	------------	X	X
Very Low Birth Weight Births	----------	------------	X	X
Preterm Births	----------	------------	X	X
Teen Birth Rate	----------	------------	X	X

Table 1 (Continued)

Births to Unmarried Mothers	----------	------------	X	X

The ordering of the models, from demographic determinants (i.e., distal) to health determinants (i.e., proximal) is adapted from the framework put forth by Mosley and Chin (1984), who proposed incorporating both social and biological variables into the same study. My analytic frame work here is that the distal determinants set the county context in which infant deaths occur and also help create the economic and health trajectories of the counties (i.e., the more proximal determinants). Therefore, ordering the models in this descending order, from most distal to most proximal, aids in interpreting results and makes the framework clearer, but does not examine how or in what ways variables at disparate levels may influence each other to shape outcomes. While the most proximal determinants, like low birth weight, are often outcomes in and of themselves, they are also determinants to other outcomes, namely infant death. My primary purpose in using this modified framework here is to better understand the many factors involved in determining rates of infant mortality and how those factors may differ between Black and white county populations. One of the primary tenets of this thesis is to examine differences in significant relationships between demographic, socioeconomic, and health variables and Black and white IMRs respectively. In order to compare the regression coefficients between the Black and white models, it is not so straightforward as simply assessing the apparent differences between the coefficients and drawing conclusions from that (Clogg 1995). It is necessary to determine whether the apparent differences observed in the regression coefficients *between* models are significant or not, using the Clogg statistic (Clogg 1995). I conducted this test for each variable which had significant coefficients across both Black and white models.

RESULTS

First, I will examine the descriptive characteristics of the infant mortality rates for both Blacks and whites as well as the demographic, economic, and health variables, then I will turn my attention to describing the relationships displayed within the OLS regression models. The mean Black IMR is 2.5 times higher than the white IMR for this sample of infant deaths, according to Table 2. This difference within highly populated urban counties is higher than the national-level disparity of Black IMRs being 2.2 times higher than whites. The standard deviation for Black IMRs is also higher than for whites, which is due to the fact that Black IMRs are highly variant, more so than whites. The highest Black IMRs are found in counties in the Northeast and in the South regions, while the highest white IMRs are found in counties in the Midwest, South, and the West regions. The lowest Black IMR of the sample, 4.93, is for Plymouth County, MA and the highest Black IMR of the sample, 16.92, is for Berks County, PA. The lowest white IMR of 1.23 is for New York County, NY, where, notably, the Black IMR is 6.86 times higher. This incredibly large disparity is not uncommon for the New York counties included in this sample. The highest white IMR of 7.75 is for Jefferson County, TX.

Table 2. Descriptive Statistics for 2012-15 Infant Mortality Rates per 1,000 Live Births in US Counties.

Variable	Mean	Std. Deviation	Minimum	Maximum
Non-Hispanic Black IMR	9.86	2.19	4.93	16.92
Non-Hispanic White IMR	3.94	1.24	1.23	7.75
N= 160				

According to Table 3, the average dissimilarity index (D) for this sample of counties (N=160) is a moderate to high value of 59.2, which indicates that, on average, 59.2 percent of people in these counties would have to move in order for racial groups to be evenly dispersed. The average IAT score is .30, and the scale for this measure is -2 to 2 with negative numbers indicating a preference for African Americans and positive numbers indicating a preference for

European Americans. This aggregated county-level sample of scores shows that the sample, on average, exhibits a slight preference for European Americans, but closer to a neutral value than to the more extreme ends of the scale. There are a few differences between the characteristics of this sample and that of national averages. The average unemployment rate for these counties is slightly higher than the national rate of 4.0, and the average median household income is approximately $2,000 lower than the national average. Both the percentages of poverty and child poverty are higher than national averages, and the teen birth rate is also higher. This is not unexpected considering that this sample is of exclusively largely populated counties including city centers, which could be expected to have higher concentrations of poverty, unemployment, and with that, lower incomes. The percentage of those who were college educated for the sample is quite similar to the national average, which ranges anywhere from 27 percent to 36 percent depending upon what age bracket is considered.

Table 3. Descriptive Statistics for Demographic, Economic, and Health Variables in US Counties.

Variable	Mean	Std. Deviation	Minimum	Maximum
Dissimilarity Index (D)	59.2	10.7	30.7	84.3
IAT Score	.30	.057	.13	.43
Percent African American	18.4	12.47	3.5	64.5
Percent Imprisoned	3.1	1.45	1.1	8.7
Unemployment Rate	5.3	1.22	3.2	10.2
Percent Female Head	14.3	3.16	8.5	31.1
Median Household Income *	5.76	1.40	3.43	11.21
Percent Poverty	15.3	4.69	6.6	31.5
Percent Child Poverty	21.8	7.27	8.0	43.0
Percent Uninsured	12.7	4.45	3.2	25.0
Percent SNAP Households	40.9	14.4	10.1	86.9
Percent College Educated	32.8	8.93	15.2	59.3
Midwives	33	36	1	233
LBW Births	996	1071.07	250	9067

Table 3 (Continued)

VLBW Births	182	190.11	41	1519
Preterm Births	1386	1505.84	315	12258
Births to Unmarried Mothers	5047	6226.01	978	57129
Teen Birth Rate	25.6	10.0	7	51
N= 160				

*Median Household Income is measured in tens of thousands of dollars.

The first regression models in Table 4 contains the demographic variables that create the social and economic context of the county in which individuals live and give birth. This model, as well as those that follow, includes the unstandardized coefficients, standard errors, the R-square values, and indicates significance levels of p<.05, p<.01, and p<.001. It also shows the results of two models, one for Black IMRs and one for white IMRs. For Black IMRs, the only variable which is significant is the percent of the county which is imprisoned (p<.05), measured as those that are in jail. The percent imprisoned is positively associated with Black IMRs meaning that as the percent of the county in jail rises, so too does infant mortality. This variable is also positively associated with white IMRs with a smaller, but still significant coefficient (p<.001). Knowing the deleterious effects of incarceration on families and communities, this finding is not unexpected, but the relationships between incarceration and infant death at the county-level have not been examined previously. The Clogg statistic is not significant for this variable across models, meaning that while there is a difference in the coefficients, that difference is not significant. The Clogg statistics for each independent variable coefficient change are displayed in Table 10 in the Appendix.

It is clear that more of these demographic variables are associated with white IMRs than Black IMRs, including the dissimilarity index and the unemployment rate. The dissimilarity index is negatively associated with white IMRs (p<.001), which means that as a county becomes *more* segregated, white IMRs decline. This provides evidence for the concentrated affluence theory of segregation for whites. The unemployment rate is positively associated with white IMRs ($p<.01$), so as unemployment rises, so do white IMRs, but this association is not found for Black IMRs. The IAT score, a measure of implicit prejudice, is not significantly associated with either groups' IMR. This measure has been found to be positively associated with other birth outcome variables previously but has not been measured in relation to infant death, that I know of. The lack of a significant finding here indicates that, while evidence shows that prejudice matters in health care and health outcomes, this particular measure of prejudice at this particular level of analysis is not associated with this particular infant health outcome. These variables do not explain a large degree of variation in either dependent variable, but they do explain a significantly higher percentage of the variation in white IMRs (25.4%) than Black (11.3%).

Table 4. OLS Regression of 2011-15 Infant Mortality Rates per 1,000 Regressed on Demographic Variables in US Counties.

Variable	Non-Hispanic Black IMR		Non-Hispanic White IMR	
Constant	4.954 (1.805)	**	4.308 (.937)	***
Dissimilarity Index (D)	.000 (.017)		-.030 (.009)	***
IAT Score	7.267 (3.903)		-1.389 (2.025)	
Percent Imprisoned	.335 (.132)	*	.250 (.068)	***
Unemployment Rate	.197 (.144)		.207 (.075)	**
Percent African American	.034 (.020)		-.004 (.010)	
R-Square	0.113		0.254	

*.05 level, **.01 level, ***.001 level

The next set of models in Table 5 and Table 6 include the economic variables and their relationships with both Black and white IMRs. Due to high levels of multicollinearity, the percent of female headed households and percent of households receiving SNAP could not be included in the same model and neither could the percent of poverty and median household income. Two different sets of models are displayed here in order to examine how the introduction of different variables changes the relationships within the models. Turning first to Table 5, the percent of the county that is college educated is negatively associated with both

Black (p<.001) and white IMRs (p<.001) and this relationship is significant for both. A one percent increase in the college education variable will result in a decrease of .076 in Black IMRs and a slightly higher decrease of .083 in white IMRs, although, according to the Clogg statistic, this difference in coefficients is not significant across models.

The percent of female headed households is negatively and significantly associated with white IMRs (p<.001) but is not associated with Black IMRs. I find that a one percentage increase in households headed by a female would result in a decrease of .121 in white IMRs. This is contradictory to the evidence which has shown that female headed households typically result in less positive outcomes for children. Potential explanations for this finding will be expanded upon later in this paper. The percent of the county in poverty is positively and significantly associated with both Black IMRs (p<.05) and white IMRs (p<.001). It makes intuitive sense that as poverty rises so would infant mortality. The difference in coefficients across models is not significant, so poverty does not matter more for Black IMRs than for whites, for example, but increases in poverty are similarly harmful for both groups. Other models [not shown here] substituted the percent of child poverty for percent poverty and found significant relationships between both Black and white IMRs (p<.01 for both) with coefficients of .102 and .038, respectively. The coefficients are slightly lower than those for percent poverty, with a larger drop seen for white IMRs than for Black. This set of variables does a significantly better job at explaining the variation in white IMRs (43.0%) but still explains very little variation in Black IMRs (14.4%).

Table 5. OLS Regression of 2012-15 Infant Mortality Rates per 1,000 Regressed on Economic Variables in US Counties.

Variable	Non-Hispanic Black IMR		Non-Hispanic White IMR	
Constant	12.934 (1.477)	***	7.084 (.682)	***
Percent College Educated	-.076 (.022)	***	-.083 (.010)	***
Percent Uninsured	-.067 (.040)		-.004 (.019)	
Percent Female Head	-.120 (.074)		-.121 (.034)	***
Percent Poverty	.130 (.052)	*	.087 (.024)	***

Table 5 (Continued)

R-Square	0.144	0.430

*.05 level, **.01 level, ***.001 level

In Table 6, the SNAP and income variables are added in place of the female headed households and poverty variables. An interesting change occurs when this is done in that college education becomes insignificant for Black IMRs. Higher levels of education can be assumed to mean higher levels of income, and this indicates that, perhaps, it is income, rather than education, which is actually affecting Black IMRs. The percent college educated remains significant for white IMRs ($p<.001$) with a negative relationship, but the coefficient does decrease in size to .056. The percent uninsured is negatively associated with Black IMRs, and this relationship is significant ($p<.05$). This variable is not associated with white IMRs. The percent of households receiving SNAP benefits is not significantly associated with Black IMRs but is with whites. This negative relationship between the variables means that as more households receive SNAP benefits, white IMRs decrease. Median household income remains one of the strongest predictors of both Black and white IMRs ($p<.001$) and is measured in tens of thousands of dollars. Income has a negative relationship with both racial groups, but the difference in coefficients across models is not significant. If the median household income of a county could be raised by $10,000, then the IMR for Blacks would drop by .677 and .455 for whites. This is quite a significant decrease and is telling of how much actual dollars in the hands of families can affect outcomes. Including SNAP and income, rather than female head and poverty, increases the amount of variation explained in both groups' IMRs to almost 20 percent for Blacks and approaching 50 percent for whites.

Table 6. OLS Regression of 2012-15 Infant Mortality Rates per 1,000 Regressed on Different Set of Economic Variables in US Counties.

Variable	Non-Hispanic Black IMR		Non-Hispanic White IMR	
Constant	16.541 (1.696)	***	9.325 (.771)	***

Table 6 (Continued)

Percent College Educated	-.036 (.024)		-.056 (.011)	***
Percent Uninsured	-.083 (.039)	*	-.015 (.018)	
Percent SNAP Households	-.013 (.015)		-.018 (.007)	*
Median Household Income	-.677 (.176)	***	-.455 (.080)	***
R-Square	0.194		0.480	

*.05 level, **.01 level, ***.001 level

The next set of models contain the health variables or the most proximal determinants to infant deaths, many of which are considered outcomes in and of themselves. The table I have included, Table 7, only includes two of those variables because many of these birth outcomes are highly correlated with each other. I will describe other significant relationships found when different variables were substituted in replacement of the ones shown. The number of practicing midwives in the county is significantly associated with both Black and white IMRs ($p<.001$) and has a negative relationship with both, but the difference in coefficients between Blacks and whites for this variable was not significant. What is most notable here is that the Midwives variable is a raw number, which means that the introduction of a single practicing midwife into a county results in a reduction in Black IMRs of .016 and a reduction in white IMRs of .010. The relationship between practicing midwives and infant death has not been examined empirically up to this point, so this is clear evidence that midwives have a significant effect on IMRs across racial groups. The teen birth rate is also significantly associated with both Black and white IMRs ($p<.001$) and has a positive relationship. The coefficients for both groups are remarkably similar, .068 for Blacks and 0.67 for whites, showing that rising teen birth rates have similar effects on rising IMRs for both groups. The amount of variation in Black IMRs that these two variables capture is similar to that found in Table 6, which is approaching 20 percent. The only models that capture more variation than those in Table 7 is the full models displayed in Tables 8 and 9. For white IMRs, 45 percent of the variation is captured by these variables.

Table 7. OLS Regression of 2012-15 Infant Mortality Rates per 1,000 Regressed on Health Variables in US Counties.

Variable	Non-Hispanic Black IMR		Non-Hispanic White IMR	
Constant	8.646 (.494)	***	2.560 (.232)	***
Midwives	-.016 (.004)	***	-.010 (.002)	***
Teen Birth Rate	.068 (.016)	***	.067 (.008)	***
R-Square	0.198		0.450	

*.05 level, **.01 level, ***.001 level

No other health variable (i.e., LBW births, VLBW births, preterm births, births to unmarried mothers) was significant for Black IMRs. For white IMRs, the number of VLBW births was significantly associated ($p<.05$) with a coefficient of .001, and the number of births to unmarried mothers was also significantly associated with white IMRs ($p<.05$) with a coefficient of .003. These coefficients are quite small and the significance levels of these two variables are also lower than what is displayed in Table 7. It is consequential that none of the birth outcome variables, outside of teen birth rate, are significantly associated with Black IMRs because this provides more evidence that it is distal factors, rather than proximal, that can make the most significant difference in ameliorating infant mortality disparities and rates.

Table 8. OLS Regression of 2012-15 Infant Mortality Rates per 1,000 Regressed on Demographic, Economic, and Health Variables in US Counties.

Variable	Non-Hispanic Black IMR		Non-Hispanic White IMR	
Constant	11.294 (2.669)	***	8.091 (.764)	***
Dissimilarity Index (D)			-.012 (.007)	
IAT Score	4.100 (3.454)			
Midwives	-.015 (.005)	***	-.008 (.002)	***
Percent Female Head	-.048 (.070)		-.089 (.028)	**
Median Household Income	-.496 (.173)	**	-.283 (.073)	***
Percent College Educated	.010 (.026)		-.036 (.010)	***
Teen Birth Rate			.034 (.010)	***
R-Square	0.255		0.599	

*.05 level, **.01 level, ***.001 level

The final models to examine are the full models that combine a number of variables from each of the first three sets of models. Again, I have included two tables, Table 8 and Table 9, to highlight how relationships change upon the introduction of different variables, since all variables cannot be included in a single model due to multicollinearity. Only two variables have a significant association with Black IMRs in Table 8, midwives ($p<.001$) and median household income ($p<.01$). Both of these variables continue to be highly associated with Black, as well as white, infant mortality. There is a negative association between Black IMRs and midwives with a slightly smaller coefficient of .015 than when the Midwives variable was included in the health model above in Table 6, exhibiting a minimal decrease in effect. Median household income is also negatively associated with Black IMRs. For white IMRs, almost all the variables in the model, with the exception of the dissimilarity index, are significantly associated. Midwives are also negatively associated with white IMRs ($p<.000$), and while not a significant difference, the coefficient of .008 is smaller than for Black IMRs. The percent of female headed households is negatively associated with white IMRs ($p<.010$), demonstrating the same seemingly contradictory relationship as in earlier models. The median household income is also negatively associated with white IMRs ($p<.001$) as it is with Blacks, and while not a significant difference, the coefficient is comparatively smaller. The percent college educated is negatively associated with white IMRs ($p<.001$), while teen birth rate is positively associated with white IMRs ($p<.001$). The relationships between independent variables and IMRs in previous models mostly hold in the full model. This set of variables explains 25.5 percent of the variation in Black IMRs and approximately 60 percent of the variation in white IMRs. For each successive model, more variation in Black IMRs is explained but it continues to lag far behind the variation explained in white IMRs.

Table 9. OLS Regression of 2012-15 Infant Mortality Rates per 1,000 Regressed on Different Set of Demographic, Economic, and Health Variables in US Counties.

Variable	Non-Hispanic Black IMR		Non-Hispanic White IMR	
Constant	9.813 (1.282)	***	6.009 (.658)	***
Dissimilarity Index (D)			-.022 (.007)	***
Percent African American	.012 (.015)			
Midwives	-.016 (.005)	**	-.007 (.002)	***
Percent SNAP Households	-.013 (.024)		-.015 (.010)	
Percent Poverty	.096 (.067)		.046 (.031)	
Percent College Educated	-.033 (.025)		-.048 (.010)	***
Teen Birth Rate			.039 (.011)	***
Table 9. (Continued)				
Percent Imprisoned	.162 (.126)			
R-Square	0.203		0.553	

*.05 level, **.01 level, ***.001 level

The final table, Table 9, demonstrates how the relationships in the full model change when percent SNAP, percent poverty, and percent African American are substituted for percent female head, median household income, and IAT Score. The percent imprisoned is also added in this final model. Here, the dissimilarity index becomes significant for whites again (p<.000) with a negative association, similar to the first demographic model albeit with a slightly smaller coefficient of .022. The Midwives variable is significant for both Black (p<.01) and white IMRs (p<.001) with a negative association for both but no significant difference in the coefficients across models. For Black IMRs, the number of practicing midwives is the only variable that is significantly associated. The percent college educated and the teen birth rate are significantly associated with white IMRs (p<.001 for both). The relationship between percent college educated and white IMRs is negative, while the relationship for teen birth rate is positive. The amount of variation explained by this set of variables decreases from the models displayed in table 8 to 20.3 percent for Black IMRs and 55.3 percent for white IMRs.

DISCUSSION

This study examined whether there were significant differences in demographic, economic, and health predictors of Black and white IMRs in highly populated counties across the United States. I found that there were more variables which were predictive of white infant mortality, and which explained more of the variation in white IMRs, than for Black IMRs. There were significant differences between the groups regarding what county-level characteristics are associated with reductions or increases in their infant mortality rates. The ways in which segregation affects specific health outcomes has not always been straightforward, but within the context of this study, I found that when the level of segregation rose, as measured by the dissimilarity index, white infant mortality decreased but Black infant mortality was not affected. There have been theories put forth concerning how concentrated affluence within white communities can improve health outcomes, which is what I find here, but this is not intended to be a policy prescription to further isolate white communities in hopes of improved IMRs. This segregation, resulting from decades of mechanisms of structural racism including redlining and other forms of discrimination, does nothing to improve Black IMRs, which are significantly higher than whites and particularly so within the counties included in this sample. Increases in the percentage of those in the county which are imprisoned also results in an increase in IMRs for both groups, which lends more evidence to claims made about incarceration's effects on communities and families. It is important to consider how we can keep families together through other types of restorative justice, rather than separating them through incarceration.

An increase in the percent of households with a female head results in a small decrease in white IMRs, which appears contradictory. Households with female heads often fare worse in more rural communities as compared to urban city centers (Snyder, McLaughlin, and Findeis 2006), so it could be the case that within the counties in this sample, which include highly populated city centers and surrounding suburbs, that female headed households have more resources than in other contexts. This does not explain why the IMRs would actually decrease for whites but speaks more to the fact that perhaps the specific resources available to and structural setting of the individuals living in these counties could play a role in this relationship. I also found in earlier models that increasing the number of households receiving SNAP benefits would decrease white IMRs, although this effect disappeared when more variables were introduced. The SNAP program has been found to be a critical component in reducing poverty and improving health (Tiehen, Jolliffe, and Smeeding 2016), but its disappearing relationship illustrates that it is not enough to solely increase the number of households eligible for benefits, but to do this in conjunction with other policy changes and initiatives.

The median household income of counties was one of the largest predictors of infant mortality rates for both Blacks and whites with significant decreases in IMRs possible. The quite simple idea of paying people more money has been put forth as a solution for poverty, and the myriad problems which arise from high levels of poverty including infant mortality, by community activists and journalists (Thomas 2017). I find this prescription to be quite true in the current study. The introduction of median household income into the models actually caused other variables that were significant to no longer be, particularly for Black IMRs, and contributed to explaining the most variation in IMRs across the country. For Black IMRs, the introduction of median household income into the model caused the effects of college education to disappear, insinuating that if communities had access to more money, then education ceases to matter to the same degree that it did previously. This relationship was not found with white IMRs, where college education remained significant even with the introduction of median household incomes.

A college degree is a known pathway to a higher-paying job than those jobs that are available to persons without a college degree, so by increasing incomes overall, education plays less of a role. Black communities across the U.S. have stunningly lower levels of income relative to other racial groups, for example a recent study by the Color of Wealth in Boston reported that the household median net worth in Boston, a county area included in this study, was $247,500 for whites and $8 for Blacks (Johnson 2017). Many were sure that this was a mistake, but it was not. This is just one of many examples of these kinds of incredible disparities in wealth and income between Blacks and whites, which structural racism mechanisms are in large part responsible for. This calls for an upstream look at the inequalities which perpetuate racial inequities in health. City and county governments should push for minimum wage increases, which would put more money in the hands of workers and families. Basic income experiments are another way that communities could aim to test the effects of rising incomes on health outcomes as well as a number of other measures. While this idea has not gained mainstream acceptance or political will just yet, perhaps, it is becoming a part of a larger conversation being had in the US. Stockton, CA is the nation's first city-led guaranteed basic income experiment, and researchers from Stanford University have disseminated a toolkit to help city leaders who are considering piloting universal basic income experiments (Bidadanure et al. 2018). More research is needed to determine the efficacy of these programs in reducing poverty, but in order to conduct research there must first be cities and counties which are willing to experiment with basic earned income for a portion of their residents. Raising the minimum wage is a more visible and nationwide movement that has been and is being implemented in many areas across the country, with San Francisco being the first city to reach a $15 minimum wage. Although these large-scale interventions are often implemented at a state-level, it is clear that large cities, like the ones contained within the counties in this study, can have a great deal of political power in leading the charge for these movements and pushing state governments in the right direction. Increases in poverty were also associated with increases in IMRs for both groups, and these policies would be methods in which poverty could potentially be decreased, leading to better health outcomes as well.

The other most significant predictor of infant mortality rates for both Blacks and whites was the number of practicing midwives in a county. I had expected to see a larger effect on Black IMRs than whites due to a number of reasons, but a primary one being that one of the goals of the midwifery model is to provide more culturally competent care to women and their infants. This would seem to be particularly important for Black women as it is no secret that institutional racism pervades medical establishments and physicians have been found to have biases against African American patients (Sabin et al. 2008), but I did not find the effects between Black and white women to be significantly different. This demonstrates that midwives are a powerful tool in reducing IMRs across racial groups and that the addition of just a single practicing midwife into a county can make a difference in birth outcomes. There are numerous challenges to achieving a goal of increasing practicing midwives including regulatory barriers on midwives' practice, insurance reimbursement, and rising costs of midwifery education accompanied by decreases in financial aid funding (Walker, Lannen, and Rossie 2014). This latter challenge is particularly problematic for diversifying practicing midwives in terms of race but also class backgrounds. If midwives are indeed going to be able to practice more culturally competent medicine, then culturally diverse midwives are needed, and significant financial burdens make this more difficult. Educating lawmakers and medical administrators on the impressive benefits of midwives on IMRs could result in changes of policy allowing midwives to practice more autonomously with less restrictions as well as increasing financial aid opportunities for midwifery education, particularly among underrepresented groups. County health departments could be a key agent in disseminating information regarding midwifery care to residents as well as lobbying local hospitals and state legislative bodies to implement larger policy changes in midwifery practice.

As for the more proximal determinants to infant mortality included among the health variables, the only one outside of midwives that was significant for Black IMRs was the teen birth rate, which was also significant for white IMRs. For white IMRs, VLBW births and births to unmarried mothers were also significant. Increases in teen birth rates resulted in increases in IMRs for both groups in this study, in part due to the fact that teenagers are most likely to be unmarried, have lower educational attainment, and lower income which are all components of adverse birth outcomes. The effects of teenage birth rates on IMRs were similar for both groups, which does not support the idea that the weathering of Black women's bodies caused in large part by systemic racism would play a role in worse birth outcomes in later life, not early life, while whites would not be affected by this. This is not meant to suggest that systemic racism plays no role in the relationships between infant mortality and other social determinants, but I do not find evidence of that for this specific case. These findings highlight the necessity of increased social supports for teenage women already pregnant and comprehensive sex education programs for teenagers across the board in order to prevent further teenage pregnancies, which county health departments are particularly well-situated to do. County health departments know the needs of residents more intimately and are better equipped to put forth interventions which will address the particular needs of their communities. The fact that no other proximal determinants of infant mortality were significant for Black IMRs, while some were for white IMRs, shows that the more distal and structural determinants are those which matter the most for Black infant death. Band-aid approaches that focus on infants who have already been born into disadvantaged circumstances preterm or at a low birth weight should not be disregarded in their efficacy, but it should be made clear that these are not sufficient in and of themselves to address high rates of Black infant mortality and ever-present racial disparities.

Focusing on the racial differences in this sample is quite important and one of the key tenets of this study, but I do not wish to overlook those things which are the same. One other critical finding of this study is the striking similarity in those variables which are significantly associated with both Black and white IMRs. There is not an appreciable difference between the effects of certain determinants on Black and white IMRs meaning that targeting these areas for improvement has the potential to greatly influence infant outcomes across both groups. Median household income and midwives, two of the variables with the strongest effects, as well as teen birth rates all have similar effects on Black and white IMRs. While there are many more determinants which are associated with white IMRs over Black IMRs and there are differences between the two, the determinants that truly matter the most for infant mortality matter similarly for both racial groups. The kinds of interventions and policy changes which I have suggested above, such as raising minimum wages, reducing regulatory and financial burdens on midwives, and increasing access to comprehensive sex education, could result in substantial decreases in infant mortality rates for all.

Limitations

One of the most evident limitations of this study is the sample size of 160 counties with the accompanying exclusion of large swaths of the United States, most notably rural America. The counties in this sample are the most largely populated in the country and tend to have more infrastructure and resources than lesser populated counties, leading to the higher possibility that interventions and policies could be empirically tested here. Also, in order to include race-specific models in the research, large sample sizes were needed which are more easily obtained from largely populated counties. However, the relationships elucidated here only apply to this sample and cannot be assumed to explain relationships between infant mortality and these variables in areas outside of these counties. Data limitations often inhibit these types of empirical investigations in rural areas, but they are possible and future research should work towards producing race-specific studies on infant mortality in those places. Because different states have varying percentages of their counties classified as urban, there is an increased likelihood that states which contain more urban counties would be included in this data set over those states with less urban counties. Specifically, due to low population numbers the Mountain region is excluded, and the Northeast region had states excluded due to low numbers of Black individuals. Other states outside of these regions which had no counties included were West Virginia and Mississippi. Because of the regional nature of the omitted counties, any bias this may introduce in terms of regional effects would be more likely towards the null (Goyal et al. 2017).

This study captures the relationships between demographic, economic, and health variables and IMRs for two racial groups, non-Hispanic Whites and non-Hispanic Blacks. This over simplifies the variation within those two groups as well as excludes multiple other racial and ethnic groups from analysis. Much of infant mortality research, as well as mortality research more generally, has been done in respect to a Black-white binary due mostly to the availability of data and larger sample sizes therein. As the US becomes a more and more diverse place, where over-simplified racial groups become less and less meaningful, how we measure race and ethnicity and how we study disparities between these groups will have to adjust as well. Other studies should seek to explore how variables such as the ones examined here affect infant mortality outcomes for other groups in the US.

All of this data is measured at the aggregate level leaving us with no information about the specific women whose births are included in the sample. This was done intentionally in an effort to move away from individual-level determinants of infant death and towards a contextual, county-level study, but, nonetheless, there are things that we cannot know about the sample, such as age ranges, education levels, or parity of the women. Multicollinearity limited the variables that could be included in the models, particularly among the health determinants, which forced me to create two separate models for some groups of variables in order to highlight relationships among all variables and the IMRs. While this did allow me to analyze how relationships changed with the introduction and removal of certain variables, it did not allow me to test how all of the variables together may have been related to Black and/or white IMRs. Many of the models and sets of variables therein did not capture significant percentages of the variation in Black IMRs in general or as compared to the variation in white IMRs. This is part of a larger research limitation, where variation in mortality among Black populations in general has been more difficult to capture in statistical models. Nevertheless, this does not provide researchers with a "pass," but, rather, should spark a commitment to continue to work towards collecting different data and operationalizing variables in differing ways in order to uncover those determinants which will assist in explaining more variation in Black IMRs. Also, the pathways through which these variables may affect infant mortality rates, or may affect each other from distal to proximal, cannot be clearly elucidated from this work but future research could employ a structural equation modeling analysis in order to determine these sorts of relationships.

Conclusion

I find that there are differences in the social determinants of infant mortality for the Black and white populations in this sample. It is clear that more of the variables included in this analysis are associated with white IMRs than with Black IMRs, and they explain more of the variation in white IMRs as well. For Black IMRs, it is critical to concentrate efforts on distal and structural determinants of infant mortality as it is here that we see the largest and most significant effects for potential decreases in IMRs. Structural racism, the idea that structures and institutions in and of themselves are racist and facilitate racial discrimination, is key in explaining why *structural* determinants matter greatly to the goal of reducing Black infant mortality, rather than more proximal health determinants. Increasing household incomes and the number of practicing midwives are two ways in which IMRs for both groups can be improved significantly, and there are clear methods that can be utilized to do both, such as increasing minimum wages and increasing financial aid availability for midwives in-training. If we are serious about reducing IMRs in general, and decreasing the racial disparity in IMRs, then we will have to look upstream to distal causes of inequality which set the context in which infants are born and die and will need to produce further knowledge and the political will to address large and systemic issues in US society.

REFERENCES

American Communities Project, Brown University. 2010. "Residential Segregation." Retrieved February 15, 2019 (https://s4.ad.brown.edu/projects/diversity/segregation2010/Default.aspx).

Arcaya, Mariana C., Alyssa L. Arcaya, S. V. Subramanian. 2015. "Inequalities in health: definitions, concepts, and theories." *Global Health Action* 8:27106. Doi: 10.3402/gha.v8.27106.

Bekemeier, Betty, Youngran Yang, Matthew D. Dunbar, Athena Pantazis, David E. Grembowski. 2014. "Targeted Health Department Expenditures Benefit Birth Outcomes at the County Level." *American Journal of Preventive Medicine* 4(6):569-577. http://dx.doi.org/10.1016/j.amepre.2014.01.023.

Bidadanure, Juliana, Sean Kline, Camile Moore, Brooks Rainwater, Catherine Thomas. 2018. *Basic Income In Cities: A guide to city experiments and pilot projects.* Stanford Basic Income Lab. National League of Cities. 1-40. Retrieved March 5, 2019 (https://basicincome.stanford.edu/sites/g/files/sbiybj7921/f/basic_income_in_cities_toolkitshareable_11-2-18.pdf).

Bonilla-Silva, Eduardo. 1997. "Rethinking Racism: Toward a Structural Interpretation." *American Sociological Review* 62(3):465-480. Doi: 10.2307/2657316.

Bonilla-Silva, Eduardo. 1999. "The Essential Social Fact of Race." *American Sociological Review* 64(6):899-906. Doi: 10.2307/2657410.

Braveman, Paula A., Shiriki Kumanyika, Jonathan Fielding, Thomas LaVeist, Luisa N. Borrell, Ron Manderscheid, Adewale Troutman. 2011. "Health Disparities and Health Equity: The Issue is Justice." *American Journal of Public Health* 101(Suppl 1):S149-S155. Doi: 10.2105/AJPH.2010.300062.

Buescher, Paul A. and Manjoo Mittal. 2010. "Racial disparities in birth outcomes increase with maternal age: recent data from North Carolina." *North Carolina Medical Journal* 67(1):16-20. Retrieved January 5, 2019 (https://www.ncbi.nlm.nih.gov/pubmed/16550987).

Bump, Philip. 2018. "In about 20 years, half the population will live in eight states." *The Washington Post,* July 12. Retrieved July 21, 2018 (https://www.washingtonpost.com/news/politics/wp/2018/07/12/in-about-20-years-half-the-population-will-live-in-eight-states/?noredirect+on&utm_term=.7550271eae35).

Clogg, Clifford C., Eva Petkova, Adamantios Haritou. 1995. "Statistical Methods for Comparing Regression Coefficients between Models." *American Journal of Sociology* 100(5):1261-1293.

Cox, Robynn. 2018. "Mass Incarceration, Racial Disparities in Health, and Successful Aging." *Journal of the American Society on Aging* 42(2):48-55.

Davis, Regina R., Sandra L. Hofferth, Edmond D. Shenassa. 2014. "Gestational Weight Gain and Risk of Infant Death in the United States." *American Journal of Public Health* 104(S1):S90-S95. Doi: 10.2105/AJPH.2013.301425.

Du Bois, William E.B. 1899. *The Philadelphia Negro: A Social Study.* New York, NY: Schocken Books.

El-Sayed, Abdulrahman M., Darryl W. Finkton Jr., Magdalena Paczkowski, Katherine M. Keyes, Sandro Galea. 2015. "Socioeconomic position, health behaviors, and racial disparities in cause-specific infant mortality in Michigan USA." *Preventive Medicine* 76:8-13. http://dx.doi.org/10.1016/j.ypmed.2015.03.021.

Eudy, Ruth L. 2009. "Infant mortality in the Lower Mississippi Delta: Geography, Poverty, and Race." *Maternal Child Health Journal* 13:806-813. Doi: 10.1007/s10995-008-0311-y.

Geronimus, Arline T. 1992. "The weathering hypothesis and the health of African-American women and infants: evidence and speculations." *Ethnicity & Disease* 2(3):207-221.

Gotanda, Neil. 1991. "A Critique of "Our Constitution Is Color-Blind."" *Stanford Law Review* 44(1):1-68.).

Goyal, Neera K., Emily DeFranco, Beena D. Kamath-Rayne, Andrew F. Beck, Eric S. Hall. 2017. "County-level Variation in Infant Mortality Reporting at Early Previable Gestational Ages." *Paediatric and Perinatal Epidemiology* 31:385-391. Doi; 10.1111/ppe.12376.

Greenwald, Anthony G., Debbie E. McGhee, Jordan L. Schwartz. 1998. "Measuring individual differences in implicit cognition: The implicit association test." *Journal of Personality and Social Pscyhology* 74(6):1464-1480. http://dx.doi.org/10.1037/0022-3514.74.6.1464.

Groffman, Peter M., Jeannine Cavender-Bares, Neil D. Bettez, J. Morgan Grove, Sharon J. Hall, James B. Heffernan, Sarah E. Hobbie, Kelli L. Larson, Jennifer L. Morse, Christopher Neill, Kristen Nelson, Jarlath O'Neil-Dunne, Laura Ogden, Diane E. Pataki, Colin Polsky, Rinku Roy Chowdhury, Meredith K. Steele. 2014. "Ecological homogenization of urban USA." *Frontiers in Ecology and the Environment* 12(1):74-81. https://doi.org/10.1890/120374.

Hauck, Fern R., Kawai O. Tanabe, Rachel Y. Moon. 2011. "Racial and Ethnic Disparities in Infant Mortality." *Seminars in Perinatology* 35:209-220. Doi:10.1053/j.semperi.2011.02.-18.

Hill, Shirley A. 2016. *Inequalities and African American Health: How racial disparities cause sickness.* Chicago, IL: Policy Press.

Hogue, Carol J. Rowland and J. Douglas Bremner. 2005. "Stress model for research into preterm delivery among black women." *American Journal of Obstetrics & Gynecology* 192(5):S47-S55. https://doi.org/10.1016/j.ajog.2005.01.073.

Hollar, David W. Jr. 2016. "Evaluating the interface of health data and policy: Applications of geospatial analysis to county-level national data." *Children's Health Care* 45(3):266-285. http://dx.doi.org/10.1080/02739615.2014.996884.

Hummer, Robert A. 1993. "Racial Differentials in Infant Mortality in the U.S.: An Examination of Social and Health Determinants." *Social Forces* 72(2):529-554.

Institute of Medicine (US) Committee on Assuring the Health of the Public in the 21st Century. 2002. *The Future of the Public's Health in the 21st Century.* Washington, DC: National Academies Press.

Johnson, Akilah. 2017. "That was no typo: The median net worth of black Bostonians really is $8." *The Boston Globe,* December 11. Retrieved March 1, 2019 (https://www.bostonglobe.com/metro/2017/12/11/that-was-typo-the-median-net-worth-black-bostonians-really/ze5kxC1Jelx24M3pugFFN/story.html).

Komro, Kelli A., Melvin D. Livingston, Sara Markowitz, Alexander C. Wagenaar. 2016. "The Effect of an Increased Minimum Wage on Infant Mortality and Birth Weight." *American Journal of Public Health* 106:1514-1516. Doi: 10.2105/AJPH.2016.303268.

Krieger, Nancy, Sofia Gruskin, Nakul Singh, Matthew V. Kiang, Jarvis T. Chen, Pamela D. Waterman, Jason Beckfiled, Brent A. Coull. 2016. "Reproductive justice & preventable deaths: State funding, family planning, abortion and infant mortality, US 1980-2010." *SSM-Population Health* 2:277-293. http://dx.doi.org/10.1016.j.ssmph.2016.03.007.

Link, Bruce G. and Jo C. Phelan. 1995. "Social conditions as fundamental causes of disease." *Journal of Health and Social Behavior* 35:80-94.

MacDorman, Marian F. 2011. "Race and Ethnic Disparities in Fetal Mortality, Preterm Birth, and Infant Mortality in the United States: An Overview." *Seminars in Perinatology* 35:200-208. Doi: 10.1053/j.semperi.2011.02.017.

MacDorman, Marian F., Donna L. Hoyert, T.J. Matthews. 2013. *Recent Declines in Infant Mortality in the United States, 2005-2011.* NCHS Data Brief, No. 120. Hyattsville, MD: National Center for Health Statistics.

MacDorman, Marian F., T.J. Matthews, Ashna D. Mohangoo, Jennifer Zeitlin. 2014. *International Comparisons of Infant Mortality and Related Factors: United States and Europe, 2010.* National Vital Statistics Reports 63(5). Hyattsville, MD: National Center for Health Statistics.

Massey, Douglas S. and Nancy A. Denton. 1993. *American Apartheid: Segregation and the making of the underclass.* Cambridge, MA: Harvard University Press.

Massey, Douglas S. and Mary J. Fischer. 2000. "How segregation concentrates poverty." *Ethnic and Racial Studies* 23(4):670-691.

Massoglia, Michael and William Alex Pridemore. 2015. "Incarceration and Health." *Annual Review of Sociology* 41:291-310. https://doi.org/10.1146/annurev-soc-073014-112326.

McFarland, Michael and Cheryl A. Smith. 2011. "Segregation, Race, and Infant Well-Being." *Population Research and Policy Review* 30(3):467-493. https://doi.org/10.1007/s11113-010-9197-7.

Montez, Jennifer Kras, Anna Zajacova, Mark D. Hayward. 2016. "Explaining inequalities in women's mortality between U.S. States." *SSM-Population Health* 2:561-571. http://dx.doi.org/10.1016/jssmph.2016.07.004.

Mosley, W. Henry and Lincoln C. Chen. 1984. "An Analytical Framework for the Study of Child Survival in Developing Countries." *Population and Development Review* 10(Supplement):25-45. Doi: 10.2307/2807954.

Murphy, Sherry L. Jiaquan Xu, Kenneth D. Kochanek, Sally C. Curtin, Elizabeth Arias. 2017. *Deaths: Final Data for 2015.* National Vital Statistics Report 66(6). Hyattsville, MD: National Center for Health Statistics.

Mustillo, Sarah, Nancy Krieger, Erica P. Gunderson, Stephen Sidney, Heather McCreath, Catarina I. Kiefe. 2004. "Self-Reported Experiences of Racial Discrimination and Black-White Differences in Preterm and Low-Birthweight Deliveries: The CARDIA Study." *American Journal of Public Health* 94(12):2125-2131. Doi: 10.2105/AJPH.94.12.2125.

National Research Council (US) Panel on Race, Ethnicity, and Health in Later Life. 2004. *Understanding Racial and Ethnic Differences in Health in Late Life: A Research Agenda.* 2004. Edited by RA Bulatao and NB Anderson. Washington DC: National Academies Press. Retrieved January 15, 2019 (https://www.ncbi.nlm.nih.gov/books/NBK24680/).

Nosek, Brian A. Frederick L. Smyth, N. Siriam, Nicole M. Lindner, Thierry Devos, Alfonso Ayala, Yoav Bar-Anan, Robin Bergh, Huajian Cai, Karen Gonsalkorale, Selin Kesebir, Norbert Maliszewski, Felix Neto, Eero Olli, Jaihyun Park, Konrad Schnabel, Kimihiro Shiomura, Bogdan Tudor Tulbure, Reinout W. Wiers, Monika Somogyi, Nazar Akrami, Bo Ekehammar, Michelangelo Vianello, Mahzarin R. Banaji, and Anthony G. Greenwald. 2009. "National differences in gender-science stereotypes predict national sex differences in science and math achievement." *PNAS* 106(26):10593-10597. www.pnas.org/cgi/doi.10.1073/pnas.0809921106.

Office of Public Health and Science, Health and Human Services. 2015. *Health, United States: 2014, with Special Feature on Adults Ages 55 to 64; Health Statistics in Brief.* United States: Government Printing Office.

Office of Management and Budget. 2000. "Standards for defining metropolitan and micropolitan statistical areas." Retrieved February 20, 2019 (http://www.census.gov/population/www/metroareas/metroarea.html).

Orchard, Jacob and Joseph Price. 2017. "County-level racial prejudice and the black-white gap in infant health outcomes." *Social Science & Medicine* 181:191-198. https://doi.org/10.1016/j.socscimed.2017.03.036.

Project Implicit. 2011. "About the IAT." Retrieved February 20, 2019 (https://implicit.harvard.edu/implicit/iatdetails.html).

Rich-Edwards, Janet, Nancy Krieger, Joseph Majzoub, Sally Zierler, Ellice Lieberman, Matthew Gillman. 2001. "Maternal experiences of racism and violence as predictors of preterm birth: rationale and study design." *Paediatric and Perinatal Epidemiology* 15(s2):124-135. https://doi.org/10.1046/j.1365-3016.2001.00013.x.

Rossen, Lauren M., Diba Khan, Kenneth C. Schoendorf. 2016. "Mapping Geographic Variation in Infant Mortality and Related Black-White Disparities in the US." *Epidemiology* 27(5):690-696, doi: 10.1097/EDE.0000000000000059.

Sabin, Janice A., Frederick P. Rivara, Anthony G. Greenwald. 2008. "Physician Implicit Attitudes and Stereotypes about Race and Quality of Medical Care." *Medical Care* 46(7):678-685.

Sabin, Janice A. Maddalena Marini, Brian A. Nosek. 2012. "Implicit and Explicit Anti-Fat Bias among a Large Sample of Medical Doctors by BMI, Race/Ethnicity and Gender." *PloS ONE* 7(11):e48448. https://doi.org/10.1371/journal.pone.0048448.

Scott-Wright, Alicia O., Ronald Matthew Wrona, Tiffany Monique Flanagan. 1998. "Predictors of Infant Mortality Among College-Educated Black and White Women, Davidson County, Tennessee, 1990-1994." *Journal of the National Medical Association* 90:477-483.

Singh, Gopal K., Michael D. Kogan, Rebecca T. Slifkin. 2017. "Widening Disparities in Infant Mortality and Life Expectancy Between Appalachia and the Rest of the United States, 1990-2013." *Health Affairs* 36(8):1423-1432. Doi: 10.1377/hlthaff.2016.1517.

Smith, Imari Z., Keisha L. Bentley-Edwards, Salimah El-Amin, William Darity, Jr. 2018. "Fighting at Birth: Eradicating the Black-White Infant Mortality Gap." *The Samuel Dubois Cook Center on Social Equity.* 1-17. Retrieved January 25, 2019 (https://socialequity.duke.edu/sites/socialequity.duke.edu/files/site-images/EradicatingBlackInfantMortality-March2018%20FINAL.pdf).

Snyder, Anastasia R., Diane K. McLaughlin, Jill Findeis. 2006. "Household Composition and Poverty among Female-Headed Households with Children: Differences by Race and Residence." *Rural Sociology* 71(4):597-624.

Speights Brown, Jodrecka S., Samantha Sittig Goldfarb, Brittney A. Wells, Leslie Beitsch, Robert S. Levine, George Rust. 2017. "State-Level Progress in Reducing the Black-White Infant Mortality Gap, United States, 1999-2013." *American Journal of Public Health* 107(5):775-782. Doi: 10.2105/AJPH.2017.303689.

Tharps, Lori L. 2014. "The Case for Black With a Capital B." *The New York Times,* November 18. Retrieved September 5, 2018 (https://www.nytimes.com/2014/11/19/opinion/the-case-for-black-with-a-capital-b.html).

Thomas, Wendi C. 2017. "Universal pre-K won't solve poverty. Better jobs will." *MLK50: Justice Through Journalism,* December 4. Retrieved March 1, 2019 (https://mlk50.com/universal-pre-k-wont-solve-poverty-better-jobs-will-3281a17e7e8f).

Tiehen, Laura, Dean Jolliffe, Timothy M. Smeeding. 2016. "The Effect of SNAP on Poverty." Pp. 49-73 in *SNAP Matters: How Food Stamps Affect Health and Well-Being,* edited by Judith Bartfeld, Craig Gundersen, Timothy M. Smeeding, James P. Ziliak. Stanford, CA: Stanford University Press.

Tyler, Elizabeth Tobin and Bradley Brockmann. 2017. "Returning Home: Incarceration, Reentry, Stigma and the Perpetuation of Racial and Socioeconomic Health Inequity." *The Journal of Law, Medicine, & Ethics* 45:545-557. Doi: 10.1177/1073110517750595.

United States Census Bureau. 2010. "2010 Urban Area to Metropolitan and Micropolitan Statistical Areas Relationship File." Retrieved January 25, 2019 (https://census.gov/geo/maps-data/data/ua_rel_download.html).

Vedam, Saraswathi, Kathrin Stoll, Marian MacDorman, Eugene Declercq, Renee Cramer, Melissa Cheyney, Timothy Fisher, Emma Butt, Y. Tony Yang, Holly Powell Kennedy. 2018. "Mapping integration of midwives across the United States: Impact on access, equity, and outcomes." *PloS ONE* 13(2):e0192523. https://doi.org/10.1371/journal.pone.019523.

Waggoner, Miranda R. 2017. *The Zero Trimester: Pre-Pregnancy Care and the Politics of Reproductive Risk.* University of California Press.

Walker, Deborah, Barbara Lannen, Debra Rossie. 2014. "Midwifery Practice and Education: Current Challenges and Opportunities." *OJIN: The Online Journal of Issues in Nursing* 19(2):4. Doi: 10.3912/OJIN.Vol19No02Man04.

Wallace, Maeve, Joia Crear-Perry, Lisa Richardson, Meshawn Tarver, Katherine Theall. 2017. "Separate and unequal: Structural racism and infant mortality in the US." *Health & Place* 45:140-144. http://dx.doi.org/10.1016.j.healthplace.2017.03.012.

Williams, David R. 2013. "Miles to Go Before We Sleep: Racial Inequalities in Health." *Journal of Health and Social Behavior* 53(3):279-295. Doi: 10.1177/0022146512455804.

Williams, David R. and Michelle Sternthal. 2010. "Understanding Racial/ethnic Disparities in Health: Sociological Contributions." *Journal of Health and Social Behavior* 51(Suppl):S15-S27. Doi: 10.1177/0022146510383838.

Williams, Kimberlé Crenshaw. 1994. "Mapping the Margins: Intersectionality, Identity Politics, and Violence Against Women of Color." Pp. 93-118 in *The Public Nature of Private*

Violence, edited by Martha Albertson Fineman and Rixanne Mykitiuk. New York: Routledge.

Xu, Kaiyuan, Brian Nosek, Anthony G. Greenwald. 2014. "Psychology data from the Race Implicit Association Test on the Project Implicit Demo website." *Journal of Open Psychology Data* 2(1):e3. http://doi.org/10.5334/jopd.ac.

Yang, Y. Tony and Katy B. Kozhimannil. 2015. "Making a Case to Reduce Legal Impediments to Midwifery Practice in the United States." *Women's Health Issue* 24(4):314-317. http://dx.doi.org/10.1016/j.whi.2015.03.006.

Yang, Y. Tony, Laura B. Attanasio, Katy B. Kozhimannil. 2016. "State Scope of Practice Laws, Nurse-Midwifery Workforce, and Childbirth Procedures and Outcomes." *Women's Health Issues* 26(3):262-267. http://dx.doi.org/10.1016/j.whi.2016.02.003.

APPENDIX. Clogg Statistic Results

Table 10. Clogg Statistic Results for All Models.

	Infant Mortality Rates				
	Black (B)		White (W)		
Independent Variables	Coeff.	Std. Error	Coeff.	Std. Error	Clogg Test B-W
Percent Imprisoned	0.335	0.132	0.250	0.068	0.572
Percent College	-0.076	0.022	-0.083	0.010	0.290
Percent Poverty	0.130	0.052	0.087	0.024	0.751
Med. Income (Table 6)	-0.677	0.176	-0.455	0.080	-1.148
Midwives (Table 7)	-0.016	0.494	-0.010	0.002	-0.012
Teen Birth Rate	0.068	0.016	0.067	0.008	0.056
Midwives (Table 8)	-0.015	0.005	-0.008	0.002	-1.300
Med. Income (Table 8)	-0.496	0.173	-0.283	0.073	-1.134
Midwives (Table 9)	-0.016	0.005	-0.007	0.002	-1.671

*A Clogg Test value of above 1.96 (absolute value) is considered significant.