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Interwoven Social Determinants:
Race, Education, and Health in the United States

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Abstract

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Educational attainment and racial assignment are essential determinants of health in the United States. Despite broad interest in how these social factors affect well-being, understanding of how they interact to simultaneously influence health is limited. Indeed, comprehension of how education manifests as a determinant of health across racial groups is largely constrained to comparisons of population averages and effect-sizes. To help develop foundations about how race, education, and health interact in the United States, I compare Black and White sample populations in terms of the effect that attaining a college degree has on self-rated health. In addition to describing how Black and White populations differ in average effects, I: (1) describe how both populations vary in how education is leveraged to protect health; (2) examine how educational gradients vary within Black and within White populations—and what differences in within-group behavior say about inequality between groups; and (3) explicate how residential context—a social feature that is organized by race in the US—modifies the association among education and health. Taken together, these three chapters demonstrate that education is a racialized social process, or that how education comes to bear on health is heavily dependent—in multiple and complex ways—upon one’s racial assignment.

TABLE OF CONTENTS

	Page
List of Figures	iii
List of Tables	v
Chapter 1: Introduction: Interwoven Social Processes	1
1.1 Introduction	1
1.2 Education and race as social determinants of health	3
1.3 The intersection of social determinants: education as a racialized social determinant of health	5
1.4 Research overview	7
1.5 References	9
Chapter 2: Inequality in Process: Income’s Role in Generating Black and White Educational Gradients in Health	16
2.1 Abstract	16
2.2 Introduction	16
2.3 Background	18
2.4 Methods	23
2.5 Data	26
2.6 Results	29
2.7 Discussion	35
2.8 References	39
Chapter 3: Inequality in Effect: Describing Black-White Heterogeneity in the Health- Protective Effects of Higher Education	48
3.1 Abstract	48
3.2 Introduction	49

3.3	Background	51
3.4	Methods	54
3.5	Data	58
3.6	Results	61
3.7	Discussion	68
3.8	References	72
Chapter 4:	Inequality in Context: Neighborhood Environments and the Association Among Education and Health	80
4.1	Abstract	80
4.2	Introduction	80
4.3	Background	83
4.4	Data	86
4.5	Methods	88
4.6	Results	90
4.7	Discussion	97
4.8	References	99
Chapter 5:	Conclusions: social conditions as simultaneous determinants of health	106
5.1	Recap and contributions	107
5.2	Limitations and future research	110
5.3	Concluding remarks	112
5.4	References	112
Appendix A:	Chapter 3 Confounders	114
Appendix B:	Chapter 4 Model Parameter Estimates	116

LIST OF FIGURES

Figure Number	Page
2.1 Model relationship among education, health, and their correlates.	24
2.2 ATE, ACDE (at median income), and ATE-ACDE for Blacks, excellent/very good health. Estimates from each imputed dataset are plotted as separate distributions. Average estimates, combined across imputations, are marked by solid line segments.	32
2.3 ATE, ACDE (at median income), and ATE-ACDE for Whites, excellent/very good health. Estimates from each imputed dataset are plotted as separate distributions. Average estimates, combined across imputations, are marked by solid line segments.	33
2.4 ACDE and ATE-ACDE for excellent/very good health, across values of income. ATE marked by dotted lines. 90% uncertainty intervals marked for ATE-ACDE estimates.	34
3.1 Conceptual model of how education and health are related.	55
3.2 Observed and estimated average effect $[ATT(a, a')]$ of attaining a college degree on the probability of reporting <i>excellent/very good health</i> . 95% uncertainty marked.	63
3.3 <i>Left</i> : Distribution of individual level educational effects $[\tau(a, a')_i]$ for excellent/very good self-rated health. <i>Right</i> : Mean-scaled $\tau(a, a')_i$ distributions.	64
3.4 Select Conditional Average Treatment Effects $[CATT(a, a', x)]$ for the probability of reporting very good or excellent self-rated health.	66
4.1 Count of neighborhoods with with x number of college educated individuals and y number of non-college educated individuals. The light-gray line represents a smoothed relationship among the two counts.	91
4.2 Distribution of neighborhood hazards and institutional quality scales among all individuals in the data. Green densities represent distributions among college educated individuals; blue-shaded densities give distributions among individuals without a college degree.	92

4.3	Estimated association (in odds-ratio; college degree/no-college degree) among education and self-rated health across CCAHS neighborhoods. Note that the solid-green line marks the average odds-ratio estimate. Grey bars represent 50% posterior intervals.	94
4.4	Predicted probability of excellent/very good health across varying levels of education and neighborhood hazards. 95% credible intervals are marked for the difference in predicted probabilities of self-rated health across education levels.	95
4.5	Predicted probability of excellent/very good health across varying levels of education and neighborhood institutional quality. 95% credible intervals are marked for the difference in predicted probabilities of self-rated health across education levels.	96
B.1	Fixed parameter estimates from logistic regression models from Chapter 4. Estimates are given in log-odds and 95% uncertainty estimates are marked.	116

LIST OF TABLES

Table Number	Page
2.1 Sample descriptive statistics, Blacks.	30
2.2 Sample descriptive statistics, Whites.	31
3.1 Summary statistics: Blacks	61
3.2 Summary statistics: Whites	62
A.1 Description of pretreatment confounders included in the analysis	115

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DEDICATION

for kcmo. you've cost me, but i love you anyways; thanks for the perspective.

Chapter 1

INTRODUCTION: INTERWOVEN SOCIAL PROCESSES

1.1 Introduction

That health is underpinned by social processes is a simple, formative insight offered by sociologists (Freese and Luftey 2011). While health outcomes are, at their endpoint, constituted within individuals, the inputs that generate them are experienced collectively and systematically. Indeed, health—and health inequity—varies within a population according to the systems of power that characterize it more generally (Hayward et. al. 2015); individuals who are marginalized by a system’s economic, political, social and ideological structures typically experience worse health than their more privileged counterparts. By shaping individual’s access to health-protective goods and experiences, social conditions act as principal *determinants of health* (Phelan et. al. 2010).

The idea that social forces are fundamental inputs to health has gained traction outside of sociology. Researchers in demography (e.g., Brown et. al. 2012), epidemiology (e.g., Berkman and Kawachi 2000), health economics (e.g., Cutler and Lleras-Muney 2006), health services (e.g., Gaskin et. al. 2012), medicine (Brosco et. al. 2013), health psychology (e.g., Uchino 2006), dentistry (Gomaa et. al. 2016) and other health-centric fields routinely quantify health gaps between individuals at different social locations.¹ The breadth of scholars producing work here means that our understanding of which social-locational positions, social resources and social experiences serve to stratify health is, in many ways, rich.

¹This idea has proliferated to the point that even non-academic medical stakeholders, who, in the past, have only been tangentially interested in social forces as causes of illness (e.g, the Association of America Medical Colleges; the United States Office of Disease Prevention and Health Promotion), have centered social determinants in their operations.

Despite broad interest in social forces as health processes, there is still room for additional analysis on the matter. Indeed, social conditions are, like the health outcomes that they affect, embedded within a larger social order; social determinants are not singular inputs, largely divorced from space and time, but instead entail many sets of complex relationships that are highly contingent upon the social structure in which they exist (Montez and Friedman 2015). To framework these intricate processes, researchers have typically ignored this embeddedness, and offered descriptions of how social condition-health relationships operate independent of concurrent social factors—including other social determinants of health. In only occasionally examining the intersection of multiple social determinants of health, our understanding of how any particular social condition operates upon health is left somewhat blunt (Montez and Friedman 2015). Research that clarifies how multiple social conditions *combine* to shape health is needed to add precision to our understanding of the social origins of population health. Investigating the simultaneous influence of multiple social conditions on health—e.g., if how an individual experiences a particular social determinant of health varies according to their other social experiences (e.g., Bowleg 2012); or if how a social-force varies in how it manifests among individuals who face different structural challenges to their health (Montez et. al. 2017)—is essential for moving health research forward.

The aim of my dissertation is to explore this idea, of interacting social determinants of population health, in more detail. In this project, I examine how two essential social inputs—*educational attainment* and *racial assignment*—combine to shape health for individuals in the United States (US). I choose to focus on education given the wealth of empirical research that demonstrates its sustained—and expanding—impact on population health outcomes (Masters et. al. 2012), and on race given extensive work that positions it as an organizing principle of US society (Bonilla-Silva 2015; Feagin 2000). In examining how, why, and under what conditions education functions to protect health among different racial groups in the US, I aim to add nuance to how both of these social

factors participate in population health.

1.2 Education and race as social determinants of health

In the contemporary United States—as well as various other temporal and geographic contexts—educational attainment is a key input to well-being (Hayward et. al. 2015). *Educational gradients*—or patterns where more highly educated individuals fare better than their less educated peers—exist among a mixture of economic resources (e.g., income; occupational opportunities), human-capital skills (e.g., cognitive functioning; meta-cognitive skills); and social/psychosocial outcomes (e.g., access to marriage; exposure to stress). These educational gradients in social well-being have become reinforced over time, with the gap between college and non-college degree holders being wider now, more than “ever in the modern era” (Pew Research Center 2014).

Through its multi-armed association with social welfare, education functions as a powerful determinant of health among the US population. The many (psycho-)social, economic, and human-capital resources derived from education coalesce into a comprehensive “health-kit,” which can be used to maintain good health across a number of scenarios (Phelan et. al. 2010; Mirowsky and Ross 2003). Indeed, due—ostensibly—to the bundle of salubrious resources that educational attainment confers, more highly educated individuals typically experience lower mortality risk and better general health status (Hummer and Hernandez 2013; Rogers et. al. 2000); fewer functional limitations (Freedman and Martin 1999); decreased risk of developing various chronic and progressive conditions (e.g., hypertension; dementia) (Sharp and Gatz 2012; Vargas et. al. 2000); and increased psychological and emotional well-being (Bauldry 2015; Erickson et. al. 2016). Similar to educational gradients in welfare more generally, the health advantages experienced by more highly educated individuals have existed in the US for decades and have become more acute over time (Masters et. al. 2012). Under certain conditions too, this association has been shown to be reflective of a causal process (e.g., Lynch and von Hippel 2016; Montez and Friedman 2015; Warren 2009). Education’s lasting, multi-

faceted, and sometimes-causal relationship with health positions it as key mechanism of population health stratification in the US.

Race is similarly central to shaping social welfare in the US. Though *racial categories* are simply socio-political groupings of individuals, defined not by biology but rather (mostly) by (arbitrary) phenotypic traits, their influence on US society is profound (Ladson-Billings and Tate 1994; Omi and Winant 1994). Indeed, the US is a *racialized social system* in that the many social, economic, and ideological subsystems that constitute it are organized in ways that are cognizant of race (Bonilla-Silva 1997). *Racial disparities* in well-being among individuals are a direct consequence of this structural arrangement; the significant and systematic racial inequity observed in many markers of welfare—including access to income (e.g., Bureau of Labor Statistics 2015); exposure to stress (Hicken et. al. 2014; Hudson et. al. 2012); exposure to environmental hazards (e.g., Crowder and Downey 2010); access to marriage markets (Crowder and Tolnay 2000); employment and occupation (Pager 2007; Vaisey 2006); educational outcomes (Walsemann et. al. 2013); and access to housing and neighborhoods (Pais et. al. 2012)—are explicitly due to the advantages that individuals coded as Non-Hispanic White experience when interfacing with US institutions, structures, and culture (Feagin 2000).

Like education, race acts upon health through its association with other dimensions of social well-being (Williams et. al. 2016). The routine disadvantage people of color face in accessing resources and in exposure to risk compound, and lead to racial disparities in a range of health outcomes. For the purposes of this project, it is important to note that health inequity is often most stark between Non-Hispanic Whites (Whites) and Non-Hispanic Blacks (Blacks) in the US. Compared to Blacks, Whites typically experience lower mortality risk and longer life-expectancy (Change et. al. 2014; Rogers et. al. 2000); better general health status (Hayward et. al. 2000); lower risk of developing various chronic conditions (e.g., hypertension) (Cutler et. al. 2008); elevated functioning along certain measures of emotional health (e.g., dysthymic disorder) (Riolo et. al. 2005); and lower risk of developing progressive conditions (Zhang et. al. 2016). (Significant

Black-White disparities manifest even in at least ostensibly mundane health outcomes, such as levels of untreated eczema) (Fischer et. al. 2017). That race stratifies all aspects of health motivates its positioning as a key determinant of population health in the US.

1.3 *The intersection of social determinants: education as a racialized social determinant of health*

Education and race are truly principle determinants of health in the US. The structural advantages experienced from holding more advanced educational credentials and from being White offer similar benefits to social well-being; these advantages compound and lead to systematic, population-wide educational gradients and racial health disparities. That education and race both operate on health through improvement to a similar array of features suggests a higher-order interaction among the two. That is, because education and race act as determinants of health through interwoven intermediaries, how education acts to influence health may necessarily be dependent on one's race and, conversely, how race functions to stratify health may be dependent on one's education (Pearson 2008). Understanding how either of these social conditions come to bear on health may necessitate understanding how they interact with one another (Williams et. al. 2016).

A compelling specification of this idea, of the inseparable connection of education and race as social determinants, is that *education is a racialized social determinant of health*. Indeed, race factors into each component that participates in education's effect on health: race stratifies access to and experiences with education; race directly affects many (of the many) resources/improvements to social-well being that serve as mechanisms of education's health effect; and race shapes what risk factors/health-challenges individuals are systematically exposed to (and thus what situations individuals would need to leverage education to protect health in). Taken altogether, the interconnectedness of race and each component of the education-health process suggests that how education functions as a social determinant of health may be quite dissimilar across racial groups in the US.

Existing empirical work on the interaction among race, education, and health is con-

sistent with the idea of education being a racialized determinant of health. Literature has consistently shown that *how much* education improves health varies among racial groups in the US. Racial subpopulations who are more marginalized by the US's social order have repeatedly been shown to experience shallower improvements to their health upon educational attainment (Crimmins and Saito 2001; Farmer and Ferraro 2005; Hayward et. al. 2000; Hayward et. al. 2015; Hummer and Hernandez 2013; Kimbro et. al. 2008; Liu and Hummer 2008; Masters et. al. 2012; Montez et. al. 2012; Walsemann et. al. 2013). The most consistent finding from this literature is that the average effect of education on health among Blacks is less than the average effect among Whites. While the exact size of this disparity varies rather dramatically across studies—from findings which suggest that Blacks receive little to no health returns to education, while Whites receive large and significant returns (e.g., Farmer and Ferraro 2005); to findings which suggest smaller, but measurable, inequity (e.g., Shuey and Wilson 2008)—research routinely shows that the difference in health between college educated Blacks and non-college educated Blacks is more narrow than the difference in health between college educated Whites and their same-race, non-college educated peers.

Beyond differences in population central tendency, knowledge of how race and education interface to shape health is limited. Indeed, because studies have overwhelmingly only described how racial populations differ in terms of average returns to education, comprehension of how race factors into the relationship among education and health is blunt; understanding of how education is a racialized social determinant of health is largely constrained to the insight that “the average Black individual receives less health benefits from educational attainment than the average White individual.” Important dimensions of the education-health relationship that may vary across racial populations—such as what mechanisms are most salient in tying education to health, or what attributes and conditions increase/limit the salubrious effects of educational attainment—are left obscured in the current literature. Developing more thorough descriptions of race-specific educational gradients would add precision to our foundational understand-

ing of how education acts to improve health among different racial subpopulations, our comprehension of how inequality manifest between racial groups, and consequentially, our ability to elaborate on how education and health interact to organize health in the US.

1.4 Research overview

In this project, to help develop foundations about the interaction among race, education, and health in the US, I examine how education varies in how it functions as a social determinant of health among Black and among White subpopulations. I specifically examine: (1) how average Black and average White educational gradients diverge in *how* they are generated; (2) how educational gradients vary *within* Black and *within* White populations—and what differences in within-group behavior say about inequality between groups; and (3) how educational gradients vary according to broader, race-salient, socio-structural factors. I describe each of the projects in more detail, below.

Chapter 2—Inequality in Process—explores how the mechanisms underlying education’s health effect vary by race. While many studies have documented that education’s effect on health is contingent upon race, few have attempted to *unpack the black box*, and describe the processes that give rise to these disparate outcomes. To make progress in understanding this inequality, I examine how a potentially key mechanism of the education-health relationship—*income*—differs in how it propagates educational gradients among Blacks and among Whites. I use data from the National Longitudinal Study of Adolescent to Adult Health (Add Health) ($n = 8,926$) and sequential g-estimation to model how a college degree’s effect on health status depends on income among Blacks and among Whites.

Chapter 3—Inequality in Effect—examines groups along measures other than just uni-dimensional means. That is, in quantifying racial disparities in education’s health effect, researchers often cleave individuals into monolithic groups, either *black* or *white*, and calculate average differences. While this type of analysis is useful, it is also agnostic to a literature that documents pronounced heterogeneity *within* Black and White pop-

ulations. (Indeed, how individuals experience *race* is conditional on other, intersecting, social characteristics—including gender, skin color, geographic-location, nativity status, and childhood SES.) To further elaborate on how race, education, and health interact in the US, empirical efforts that recognize this higher-order complexity are needed. To this end, in *Chapter 3*, I examine: (1) how variable the health-returns to a college degree are *within* Black and *within* White sample populations, as well as (2) *which members* of each racial-group experience the greatest health-benefits from completing a college degree.

Chapter 4—Inequality in Context—examines how broader social structures, that are patterned around race, factor into educational gradients in health. An emerging literature suggests that the contextual environment may play a role in shaping educational gradients in health; by influencing what health-risks individuals are exposed to and what shared-resources individuals have available to them, spatial context is hypothesized to dictate the set of health-challenges that an individual would need to use their education to protect against. This interaction—among personal educational attainment, context, and health—may be particularly important for understanding health among Blacks, for who the positive association among education and salubrious contextual traits is decoupled relative to Whites. If neighborhood context is central to shaping educational gradients, and race is essential to shaping access to neighborhoods, than understanding how neighborhood context affects educational gradients is essential for understanding how race features into education’s health effect. *Chapter 4* develops this idea by examining: (1) how variable educational gradients are across neighborhood contexts; (2) how educational disparities in health vary with elevated exposure to neighborhood-propagated health-challenges; and (3) how educational disparities in health vary across neighborhoods with differing levels of high-quality resources. I use data from the Chicago Community Adult Health Study and Bayesian multilevel logistic regression models for this analysis.

In each empirical chapter, I find that race alters how education acts as social determinant of health. *Chapter 5* offers a discussion of these findings within the broader popula-

tion health literature.

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Chapter 2

INEQUALITY IN PROCESS: INCOME'S ROLE IN GENERATING BLACK AND WHITE EDUCATIONAL GRADIENTS IN HEALTH

2.1 *Abstract*

Extensive literature documents Black-White heterogeneity in the health-protective effects of education; though education is a salient social determinant among both groups, Whites appear to benefit more from additional schooling than do Blacks. While many studies have documented this disparity, few have attempted to *unpack the black box*, and describe the processes that give rise to these disparate outcomes. To make progress in understanding this inequality, I examine how a potentially key mechanism of the education-health relationship—*income*—differs in how it propagates educational gradients among Blacks and Whites. I use data from the National Longitudinal Study of Adolescent to Adult Health ($n = 8,926$) and sequential g-estimation, to model how a college degree's effect on health status depends on income among Blacks and among Whites. I find that income varies, markedly, across groups in how it participates as a mechanism of education's health effect, and that this differential behavior provides one possibility as to why racial disparities exist in education's health effect.

2.2 *Introduction*

Education is, in context of the United States (US), a key input to well-being. *Educational gradients*—i.e., patterns such that individuals with higher levels of education fare better than their less educated peers—exist among a mixture of outcomes in this population. From the economic (e.g., increased annual earnings) to the psychological (e.g., improved emotional well-being), educational attainment returns individuals an array of substantial

advantages (Goldin and Katz 2008; Mirowsky and Ross 2003).

The association among education and well-being is of special importance in population health. The social, economic, and psychological benefits associated with educational attainment are believed to coalesce, and lead to pronounced educational health gradients (Montez and Friedman 2015). By offering individuals a diverse toolkit through which to protect their health, education is conceptualized as a key mechanism of population-health stratification (Phelan et. al. 2010). Consequently, this social input is sometimes positioned as a promising point of intervention for widespread social change; macro-level, education-based interventions (e.g., reducing barriers to college entry) might equip a population of individuals with a bundle of resources that could be used to maintain health in a variety of contexts (Cohen and Syme 2013).

Like most complex social processes in the US, the association among education and health is also characterized by significant, social-locational based inequalities (e.g., Montez et. al. 2017; Rogers et. al. 2000; Zajacova and Hummer 2009). In terms of race, disparities that mirror larger patterns of inequality—i.e., in that Whites experience greater returns than people of color—have been observed in this process (Kimbrow et. al. 2008). Because education is a key mechanism through which good health is maintained, racial disparities in the health returns to education act to propagate racial disparities more generally, across all levels of socioeconomic status (Williams et. al. 2016). Moreover, racial inequality in this relationship limits education's potential for catalyzing population-health change. While increasing educational attainment among the population may improve health overall, it may also exacerbate existing racial disparities, if done so bluntly (Woolf and Braveman 2011). Explicating *why* and *how* inequalities in the health returns to education are generated is thus an important task for population health scientists (Hayward et. al. 2015).

This paper is part of a larger project that attempts to flesh out our limited understanding of why racial disparities in educational health gradients exist. In this study, I examine how a mediator of the education-health relationship—i.e., *income*—differs among Blacks

and among Whites, in how it participates as a mechanism of a college degree's effect on health status. To examine this, I use data from The National Longitudinal Study of Adolescent to Adult Health (Harris et. al. 2009), and sequential g-estimation, a method for identifying controlled direct effects in the presence of intermediate confounders (Vansteelandt 2009). By better identifying how the process that gives rise to educational gradients diverges across racial groups, we may make progress in narrowing gaps in educational gradients, as well as racial disparities in health more generally.

2.3 Background

Education is an (extraordinarily) powerful predictor of health in the US. Individuals with higher levels of educational attainment experience lower mortality risk and better general health status (Hummer and Hernandez 2013; Rogers et. al. 2000); fewer functional limitations (Freedman and Martin 1999); decreased risk of developing various chronic and progressive conditions (e.g., hypertension; dementia) (Sharp and Gatz 2012; Vargas et. al. 2000); and increased psychological and emotional well-being (Bauldry 2015; Erickson et. al. 2016). This pattern, of more highly educated individuals possessing better health, has persisted in the US for decades, has become more pronounced over time (Miech et. al. 2011) and, under certain conditions, has been shown to be reflective of a causal relationship (Lynch and von Hippel 2016; Montez and Friedman 2015).

Perhaps the most striking feature of the education-health relationship is the bundle of mechanisms that are hypothesized to participate in it. For example, education offers individuals an number of health-protective economic resources. Attaining additional educational credentials, typically, increases one's earnings which, in turn, can be used to purchase greater amounts of/higher quality health-protective inputs (e.g., quality health insurance; housing in advantageous neighborhoods) (Lynch 2006). Similarly, education increases the likelihood that one might avoid prolonged periods of unemployment (which can lead to health degrading chronic stress), and increases one's chances of attaining a high prestige occupation (which can lessen exposure to health adverse working condi-

tions and increase self-esteem) (Fujishiro et. al. 2012; Mirowsky and Ross 2003).

Non-material features too, are thought to generate educational gradients in health. For instance, meta-cognitive skills (e.g., *mastery*, or the extent to which an individual regards their life-chances as being under their own control) (1) are developed through educational attainment, and (2) help individuals manage stress and buffer against adverse-exposures that might otherwise result in poor health (Gallo and Matthews 2003; Kawachi et. al. 2010). Cognitive resources are hypothesized to work similarly, increasing one's ability to navigate difficult health situations (Mirowsky and Ross 2003). Human capital resources like these are situated within in the individual, and thus offer an "ever-present" means of protecting against poor health. Education also increases one's likelihood of marriage (which can be a salubrious social tie), and shapes one's social network in ways that promote health (Cutler and Lleras-Muney 2006).

Because education: (1) positively affects multiple health outcomes; (2) has influenced health for decades, despite shifts in more proximate health-determinants; and (3) operates on health through many mechanisms, it is often positioned as a *fundamental cause of health inequality* (Freese and Luftey 2011; Phelan et. al. 2010). How individuals experience health in the US is—and has for sometime been—deeply dependent on their level of educational attainment. While characterizing education in this way is helpful—in that it highlights education's remarkable role in shaping population health—one must be careful to distinguish *fundamental* from *universal* or *uniform* (Bowleg 2012; Freese and Luftey 2011; Pearson 2008). That is, because education is tied to health through an array of mechanisms, that are each embedded within a larger social context, the process that generates better health per increased education is dependent on one's social location, particularly one's race.

The Intersection of Multiple Social Determinants: Race, Education, and Health in the United States

Historical moments of domination (e.g., slavery; colonialism; forms of labor importa-

tion) have served to create *race*, or socio-political categories of individuals defined (mostly) by (arbitrary) phenotypic traits (Bonilla-Silva 2015; Feagin 2000). The US is a *racialized social system* in that stratification exists among these socially-defined categories: multiple social, economic, and ideological institutions within the US are arranged in ways that often (re-)produce advantages for individuals coded as Non-Hispanic White, and disadvantages for individuals coded otherwise (Bonilla-Silva 1997).

For the purposes of this project, it is important to note that many, if not all, of the resources that are thought to propagate education's health effect are fashioned by racialized institutions in the US—and thus experienced differently by individuals sorted into different racial groups (Williams et. al. 2016). For instance, due to a multitude of factors—including permeative ideology that characterizes workers in ways that (de-)legitimize their claims to higher wages (Avent-Holt and Tomaskovic-Devey 2013)—individuals in different racial groups have access to substantially different levels of income, even at the same level of education. (e.g. in 2014, where the median weekly income of White individuals with at least a college degree was \$1,132, the median weekly incomes of Black and of Latinx individuals with at least a college degree were \$970 and \$1,007, respectively) (Bureau of Labor Statistics 2015). Differences in income go beyond access too, with structural features (e.g., residential segregation) constraining *purchasing power*, or the amount/type of resources that individuals of color might purchase (e.g., for Blacks, housing in advantageous neighborhood environments that their incomes might otherwise allow them access too) (Pais et. al. 2012). Structural features similarly cause individuals of color to face barriers in attaining occupations that match the prestige of their educational credentials (e.g., Pager 2007; Vaisey 2006); attenuated employment-related benefits (e.g., Acker 2006; Wingfield 2009); over-taxed meta-cognitive reserves (e.g., Hicken et. al. 2014; Hudson et. al. 2012); and diminished marital returns to education (e.g., Crowder and Tolnay; Thomas 2015), relative to Whites.

Because the mechanisms that tie education to health are experienced so differently across racial groups, one might predict that education—as it operates as a social determi-

nant of health—is a racialized social process. That is, given that *substantial* racial variation exists in *many (of the many)* resources that tie education to health, it is highly probable that how—and how much—individuals benefit from educational attainment varies by race. Prior research, particularly on Non-Hispanic Blacks and Non-Hispanic Whites, is consistent with this idea (Hayward et. al. 2015).

A number of empirical studies have shown that the strength of the association among education and health varies by race, such that groups who are marginalized in the US social order typically experience shallower gradients (Crimmins and Saito 2001; Farmer and Ferraro 2005; Hayward et. al. 2000; Hayward et. al. 2015; Hummer and Hernandez 2013; Kimbro et. al. 2008; Liu and Hummer 2008; Masters et. al. 2012; Montez et. al. 2012; Walsemann et. al. 2013). While a number of different racial groups and health outcomes have been examined here, research has most consistently demonstrated that educational gradients in general health status (e.g., mortality; self-rated health) are less steep among Non-Hispanic Blacks (Blacks) than Non-Hispanic Whites (Whites). In Hummer and Lariscy's (2011) estimation, for example, middle-aged, college educated Blacks have a 0.80 times lower hazard of mortality than high-school educated Blacks of the same age, where middle-aged, college educated Whites have a 0.72 times lower hazard of death than their high-school educated counterparts. Similarly, Shuey and Wilson (2008) show that while each year of educational attainment moves Blacks 0.07 points down a 5-point scale of self-rated health (ranging from 1 = *excellent health* to 5 = *poor health*), Whites move down the same scale at a rate of 0.11 points per year of schooling. Note that while education appears to be more strongly related to health status for Whites across the range of education, the most pronounced racial disparities appear to exist at the higher end of the educational spectrum (e.g., among college degree holders) (Hummer and Hernandez 2013).

Though it is clear that educational gradients are race-contingent, and while it can be intuited that this heterogeneity is due to pronounced, structurally-mediated, differences in how individuals experience the mechanisms that lie intermediate education and

health, empirical work which clarifies the latter idea is sparse (Hayward et. al. 2015; Walsemann et. al. 2013). Indeed, Black-White differences in the *strength* of the relationship among education and health imply Black-White dissimilarity in the *machinery* that generates better health per increased education. Yet studies that clarify how any particular resource participates as a mechanism of education's health effect, how mechanisms vary in salience across racial groups, and, consequently, which mechanisms are most responsible for generating racial inequality are limited. Race-specific educational gradients—and arguably, educational gradients more generally—are largely empirical black-boxes.

Only a handful of studies have examined how the underlying machinery that ties education to health varies by race (Backlund et. al. 1999; Hayward et. al. 2015; Montez et. al. 2012). Using data from the 1979-1998 National Longitudinal Mortality Study, for instance, Montez et. al. (2012) assess several parametric specifications of the educational gradient in mortality among different racial groups. The authors find that Blacks benefit most from education during years where credentials are typically earned (e.g., after 16 years, in which a high school degree is often earned) and that Whites generally see linear returns to each year of schooling. Montez et. al. (2012) infer, from these shapes, that Blacks are more reliant on credential-related resources returned from education, where Whites are more readily able to translate human capital returns into good health. Using the same analytical approach, on more recent data, Hayward et. al. (2015) find, generally, similar results and conclude that what resources individuals draw upon to use education to protect health varies by race.

While studies like Montez et. al. (2012) and Hayward et. al. (2015) are insightful, the fact that they rely upon indirect inference leaves room for additional analysis. In comparing the shape of educational gradients across groups, these studies are only able to make broad statements about how the process underlying health returns to education vary by race (e.g., that *some type of non-material resource is more important in generating gradients among Whites*). Our understanding of which specific features are more/less salient in

propagating educational gradients among Blacks and Whites—and thus which features are most responsible for creating racial inequality in this process—is left obscure. To further unpack this black box, direct tests of how specific resources serve to propagate educational gradients among Blacks and among Whites are needed.

Current Study

To begin to unpack racially-disparate educational gradients, I describe how a key mediator of the education-health relationship—*income*—differs among Blacks and among Whites in how it participates as a mechanism of a college degree's effect on health status. I examine how the effect of education would diminish if educational attainment did not come with an increase in earnings, how this behavior varies among Blacks and Whites, and whether Black-White differences in how income functions as a mechanism in education's health effect helps explain Black-White heterogeneity in education's health effect.

Income is chosen as a starting point, in this broader project of unpacking racial inequality, given its potential importance in clarifying Black-White disparities in educational gradients. That is, income is often assumed to be *the* core mediator of the education-health relationship. In certain contexts—and only under very strong assumptions—income has been shown to explain upwards of 30% of education's effect on health (e.g., Lynch 2006). Because income is hypothesized to explain large portions of why education is tied to health, small differences in how it functions could result in large differences in overall gradients. Because, as explain above, signifigacnt racial variation does exist in how this feature is experienced—i.e, Blacks experience attenuated income returns to education and barriers in leveraging income towards further salubrious resources—I predict that income will vary significantly in how it serves to propagate educational gradients and consequently, helps clarify why Black-White disparities exist in educational gradients.

2.4 Methods

Analytical Framework

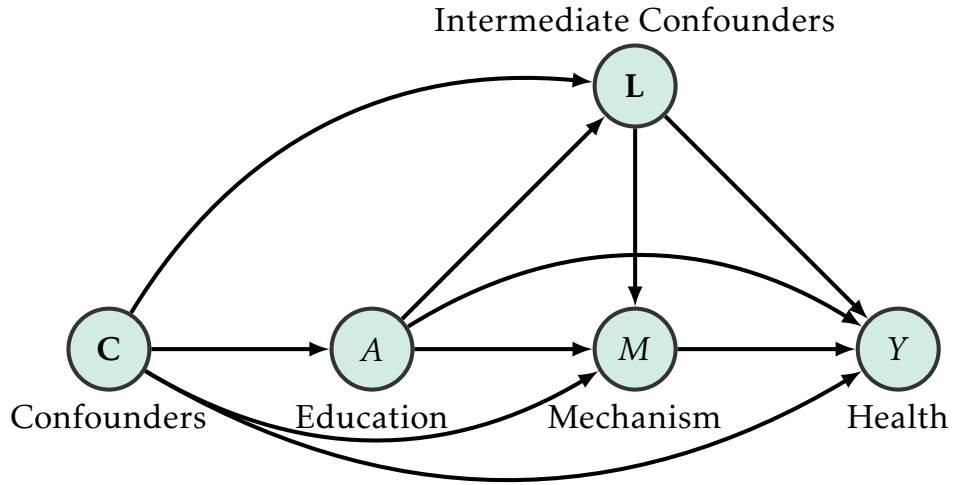


Figure 2.1: Model relationship among education, health, and their correlates.

To fix ideas, the simple diagram presented in Figure 2.1 displays the relationship between education and health, and the confounders that surround it.

For each racial group, I estimate the *average treatment effect of a college degree on health* (i.e., the ATE), or:

$$ATE(a, a') = E[Y_i | A_i = a, C_i] - E[Y_i | A_i = a', C_i]. \quad (2.1)$$

The $ATE(a, a')$ gives a difference in counterfactual states (Rubin 2005): $E[Y_i | A_i = a, C_i]$ represents the average health outcome (Y) of a group of individuals ($1, \dots, i, \dots, n$) who received a college degree ($A = a$), while $E[Y_i | A_i = a', C_i]$ gives the average health of the same individuals—with the same background traits (C_i)—had they not received a college degree ($A = a'$). The estimated difference in these two quantities summarizes the effect that attaining a college degree has on health.

I also estimate, for each racial group, the *controlled direct effect of a college degree on health* (i.e., the ACDE), or:

$$ACDE(a, a', m) = E[Y_i | A_i = a, M_i = m, C_i] - E[Y_i | A_i = a', M_i = m, C_i]. \quad (2.2)$$

Like the ATE, $ACDE(a, a', m)$ gives the estimated difference in health for individuals had they and had they not received a college degree. The difference here is that the ACDE fixes the mechanism of interest M to be equal across counterfactuals. The ACDE thus summarizes the effect of attaining a college degree if income were fixed at a particular level for all individuals, *regardless of their education* (Acharya et. al. 2016). This quantity can be thought of as the total effect of education on health that is not due to income (either as an indirect effect or an interaction effect) (Acharya et. al. 2017; VanderWeele 2014).

The difference between the ATE and the ACDE provides a summary of the educational effect that would remain under an intervention that fixes a mediator to a specific value (VanderWeele 2016). Put differently, $ATE(a, a') - ACDE(a, a', m)$ represents an aggregation of two effects: (1) an indirect effect (i.e., how much a college degree affects income, and subsequently how much income affects health); and (2) an interaction effect (i.e., how much income enhances the direct effect of education, or the effect of education not mediated through income) (Acharya et. al. 2016; VanderWeele 2014). Without making additional assumptions—that are often far beyond any social science question (Imai et. al. 2011)—further separating out these two effects is infeasible. While the difference in the ATE and the ACDE offers a broad summary of how a resource participates as a mechanism, the fact that is identifiable under reasonable assumptions makes it useful for this paper (Acharya et. al. 2016).

In this analysis, I estimate the ACDE at its mean—which, if we assume that the aforementioned interaction effect is the same between any two levels of income, gives a reasonable approximation of an indirect effect (Acharya et. al. 2016)—and across values of M —to investigate how the controlled direct effect of a college degree varies at different levels of income. Generally speaking, greater deviations from the ATE indicate that a feature is participating more—whether as an indirect or interaction effect—in generating education’s health effect (Acharya et. al. 2017).

Sequential G-estimation

The presence of intermediate confounders (L) (i.e., features that are influenced by education, and affect income and health) complicates the estimation of the ACDE. Either ignoring intermediate confounders all together, or adjusting for them via conventional regression could lead to biased results (e.g., post-treatment bias) (Gelman and Hill 2007; Rosenbaum 1984). For example, take L as a respondent’s occupation. As occupation influences earnings and health, conditioning on income while ignoring occupation would risk inducing spurious associations among education, intermediate confounders, and health (Rosenbaum 1984). Controlling for occupation in a traditional regression model to account for this however, would block part of the controlled direct effect ($A \rightarrow L \rightarrow Y$), which is problematic as we only wish to adjust for M (Acharya et. al. 2016).

Given the above concerns, I estimate the ACDE using sequential g-estimation (Acharya et. al. 2016; Vansteelandt 2009). This method proceeds in two steps. In Step 1, a regression model, $Y \sim f(A_i, M_i, C_i, L_i)$, is fit to estimate the effect of the mediator M on the health outcome Y , conditional on all other variables. (In the model $Y_i = \beta_0 + \beta_1 A_i + \beta_2 M_i + \beta_3 C_i + \beta_4 L_i$, for instance, $\beta_2 M_i$ is this effect). In Step 2, each individual’s health outcome Y is “de-mediated” to produce \hat{Y}_i ; that is, the effect of the mediator obtained in Step 1 is subtracted from Y_i . (Returning to the previous example, this means $\tilde{Y}_i = Y_i - \beta_2 M_i$). The de-mediated outcome \hat{Y}_i is then regressed on the the treatment and pretreatment confounders to estimate $E[\tilde{Y}_i | A_i, C_i]$. This final quantity is an estimate of the average controlled direct effect, that avoids bias from conditioning on post-treatment variables (Acharya et. al. 2016). A nonparametric bootstrap, that repeats both steps of the method, is used to obtain 90% uncertainty estimates.

2.5 Data

The National Longitudinal Study of Adolescent to Adult Health

Data come from the National Longitudinal Study of Adolescent to Adult Health (Add Health). Add Health is an ongoing, nationally-representative, school-based study of adolescents in grades 7 to 12 that began in 1994 (Harris et. al. 2009). Add Health currently

includes four waves of data: Waves 1 (W1: 1994-95); 2 (W2: 1996); 3 (W3: 2001-02); 4 (W4: 2007-08). In W4, respondents ranged in age from 24-32 years old.

The utility of Add Health, for this project, is two-fold. First, Add Health is useful in that allows me to distinguish *pretreatment*, *treatment*, and *post-treatment* periods, with some clarity. Delimitation of these periods means that I can better identify the correct causal ordering of the necessary variables (as represent in Figure 1). The second benefit of these data come from their richness. At each, wave, Add Health collects hundreds of detailed measures of social, economic, psychological, and health related factors. The richness of Add Health’s measures at each wave allows me to represent all components of Fig. 1 in detail.

Measurement

To define the three periods (i.e., pretreatment, treatment and post-treatment) needed to identify Fig. 1, I divide Add Health into separate time segments. The time segment after W1 and before W4 of the data are taken to be the treatment period, where individuals are “assigned” an education level. Fixing this time period helps define all renaming periods: features that occurred prior to or during W1 can be considered pre-treatment (and thus a source of *C*) and features that occur at W4 can be considered post-treatment (and thus a source of *L*, *M*, and *Y*). Below, I describe the variables used to define these sets.

Treatment (*A*): Education

For this analysis, I define education according to whether an individual completed a college degree in the treatment period. Individuals who completed, at least, a college degree were assigned $A = 1$, while individuals who completed, at most, a high school degree (i.e., just a high school degree + some college) were assigned $A = 0$.¹ Respondents who

¹More conservative groupings (e.g., only completed a college vs. only completed a high school degree) produced similar results to what is discussed below

where still enrolled in school at W4, and individuals who completed their educational attainment prior to W1 are dropped from this analysis.

Outcome (Y): Self-Rated Health

Health is measured as W4 self-rated health status. Respondents were asked to describe their health as either *excellent*, *very good*, *good*, *fair*, or *poor*. Like many other researchers who use this measure (e.g. Braveman et. al. 2011), I group adjacent categories to represent broad regions of health: *excellent/very good health* vs other and *fair/poor* vs. other. I choose this outcome given: (1) the measurable racial differences that exist in its association with education (see above); and (2) because of its correlation with other outcomes for which racial heterogeneity exists in educational gradients (e.g., mortality) (Idler and Benyamini 1997). (Sensitivity analysis show that grouping *good* health with *fair/poor* or *excellent/very good* health produces substantively similar results.)

Mechanism (M): Income

(Annual) income is measured at W4. Individuals were asked, *over the past year, how much income did you receive from personal earnings before taxes, that is, wages or salaries, including tips, bonuses, overtime pay, and income from self-employment?*. Responses were taken as measure of annual earnings (in log dollars). Income is winsorized at \$5,000 and \$150,000 (like other Add Health income measures) to lessen the influence of extreme values on our parameters (Gelman and Hill 2007). Specification tests, based on Akaike's Information Criterion (AIC), suggest that a squared version of income is appropriate in models for Whites.

Pretreatment (C) and Post-treatment (L) Confounders

Pretreatment confounders (C) are features that influence educational attainment and W4 health. For this analysis, I define this vector of traits as: *self-reported sex category* (1 if male; 0 if female); W4 age (in years); *parent college status* (1 if has parent with a college

degree; 0 if not); *W1 self-rated health status* (1 if in excellent/very good health; 0 if otherwise); *W1 depressive symptomatology* (as measured by the Center for Epidemiologic Studies Depression Scale 9-item scale); *W1 Peabody Picture-Vocabulary Score* (in percentile rank compared to same age peers); *W1 college expectation* (in how likely a respondent thinks it is that they'll attend college; from -2 very little chance to +2 very high chance) *average class size* (at school attending in W1); *block income* (in log dollars, of residence at W1); and *W1 region of residence*; (1 South; 0 if otherwise). *Race* (either *Non-Hispanic Black* or *Non-Hispanic White*) is defined from self-reports. A handful of individuals born outside of the US were dropped from the analysis.

Post-treatment confounders (**L**) are defined in W4 as: *W4 occupation* (1 if last occupation was in a managerial or professional occupation; 0 if otherwise); *W4 marital status* (1 if married; 0 if otherwise); *W4 employment* (1 if employed; 0 if not); and *W4 number recall test score* (from 0 to 7).

Missing Data

To retain individuals with missing responses, and avoid bias that might arise from listwise deletion, we employ the *Amelia* algorithm (Honaker et. al. 2001) for multiple imputation. We adjust this method to fit within a bootstrap framework following Schomaker and Heumann's (2016) guidelines, particularly their *MI Boot* recommendation. This strategy entails: (1) creating J imputed datasets using *Amelia*; (2) drawing B bootstrap samples from each imputed data set; (3) calculating, bootstrapped, quantities of interest (e.g., the standard error of the ACDE) within each imputed set; and combining quantities from each set using Rubin's Rules (Schomaker and Heumann 2016). We use $J = 10$ imputations, and $B = 200$ bootstrap samples from each, in this process.

2.6 Results

To contextualize our sample, Table 2.1 and Table 2.2 provide descriptive statistics for Blacks and Whites, respectively. These tables show that, as expected, college educated

individuals fared better on most pretreatment features than their less educated counterparts. Among both racial groups, individuals who completed a BA in the treatment period had better starting physical/mental health; were from higher SES families and areas; and performed better on cognitive tests. College educated respondents similarly fared better on post-education outcomes in both groups; individuals with only a high school degree at W4 had worse self-rated health, lower incomes, were less likely to marry, and had lower cognitive test scores. Note that pronounced Black-White differences exist among college educated individuals. Whites with a college degree had elevated levels of self-rated health, were more likely to be married, and had higher incomes than their Black, college-educated peers.

Table 2.1: Sample descriptive statistics, Blacks.

variable	without BA ($n = 1,648$)	with BA ($n = 701$)
	mean (s.d)	mean (s.d)
W4 age	28.54 (1.80)	28.27 (1.76)
Female	0.50 (-)	0.64 (-)
Parent with BA	0.30 (-)	0.58 (-)
W1 superlative SRH	0.70 (-)	0.78 (-)
W1 depression	6.48 (4.2)	4.95 (3.88)
W1 expect college	1.03 (1.2)	1.70 (0.67)
W1 picture-vocabulary score	0.31 (0.2)	0.51 (0.27)
W1 average class size	27.50 (5.60)	26.94 (5.48)
W1 block income	\$24k \$(14k)	\$28k \$(15k)
W1 in South	0.62 (-)	0.57 (-)
W4 superlative SRH	0.50 (-)	0.62 (-)
W4 income	\$25k (\$20k)	\$41 (\$25k)
W4 number test score	3.69 (1.51)	4.36 (1.54)
W4 married	0.20 (-)	0.30 (-)
W4 more prestigious occupation	0.15 (-)	0.63 (-)
W4 unemployed	0.20 (-)	0.09 (-)

Table 2.2: Sample descriptive statistics, Whites.

variable	without BA ($n = 4,162$)	with BA ($n = 2,415$)
	mean (s.d)	mean (s.d)
W4 age	28.51 (1.79)	28.32 (1.74)
Female	0.49 (-)	0.58 (-)
Parent with BA	0.25 (-)	0.61 (-)
W1 superlative SRH	0.63 (-)	0.82 (-)
W1 depression	5.89 (4.24)	4.52 (3.71)
W1 expect college	0.90 (1.24)	1.76 (0.59)
W1 picture-vocabulary score	0.54 (0.25)	0.71 (0.22)
W1 average class size	24.72 (4.64)	24.64 (4.98)
W1 block income	\$30k (\$11k)	\$35k (\$15k)
W1 in South	0.35 (-)	0.30 (-)
W4 superlative SRH	0.53 (-)	0.76 (-)
W4 income	\$30k (\$24)	\$47k (30k)
W4 number test score	4.15 (1.46)	4.71 (1.43)
W4 married	0.49 (-)	0.51 (-)
W4 more prestigious occupation	0.20 (-)	0.65 (-)
W4 unemployed	0.18 (-)	0.08 (-)

The next set of results—represented in Figures 2.2 and 2.3—give the ATE of *excellent/very good health*, the ACDE (at median income), and the difference between the two (which can be a reasonable estimate of the indirect effect of income), for Blacks and Whites:²

²Note that these figures give the probability of being in superlative health. Results for the other category of interest (*fair/poor health*) offer the exact same perspective, and thus are held back to conserve space.

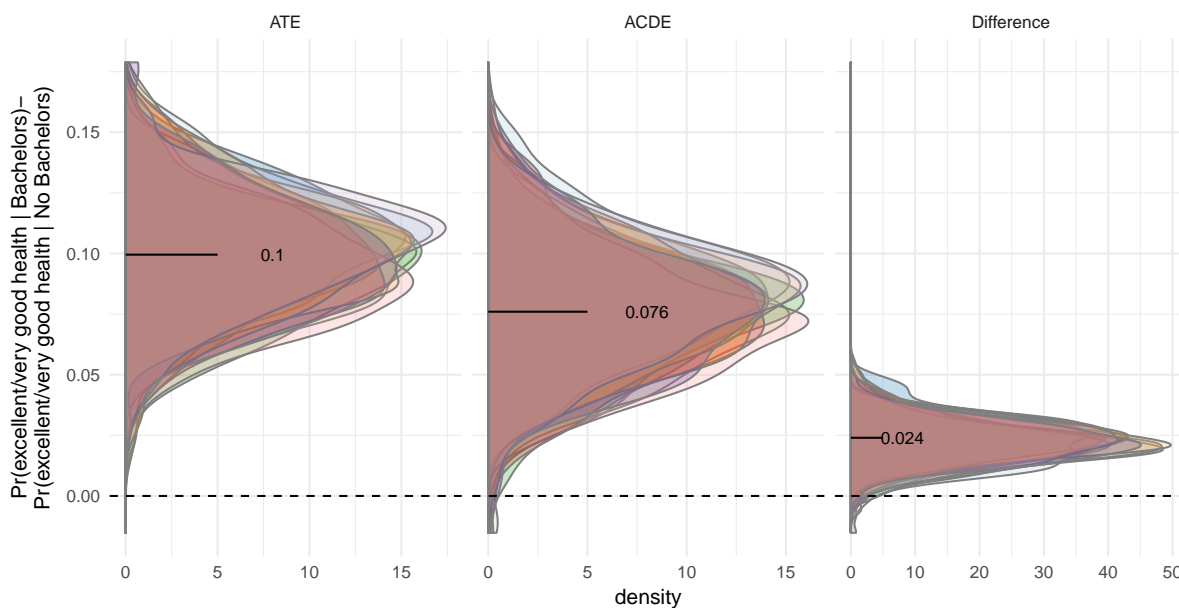


Figure 2.2: ATE, ACDE (at median income), and ATE-ACDE for Blacks, excellent/very good health. Estimates from each imputed dataset are plotted as separate distributions. Average estimates, combined across imputations, are marked by solid line segments.

Figure 2.2 shows that among Blacks at median levels of income, controlling for income has a significant impact on the association among education and self-rated health. The ATE shows that individuals with a college degree are 10-percentage points more likely to be in *excellent/very good health* than respondents without a college degree. The ACDE shows that when income is fixed to the sample median (about \$25k) for all members of the population, the ATE diminishes by about 0.025 points (or about 25%). As displayed in the last panel of Figure 2.2, this change is significant; the 90% confidence interval around the estimated ATE-ACDE is (0.01, 0.05). This difference suggests that, in the average case, income plays a significant role in creating education's effect on health among Blacks. Here, income serves either as an indirect effect (i.e., that income increases after earning a college degree, and those earnings positively affect health), as an interaction effect (e.g., that income has some positive effect on the strength of the alternative, non-

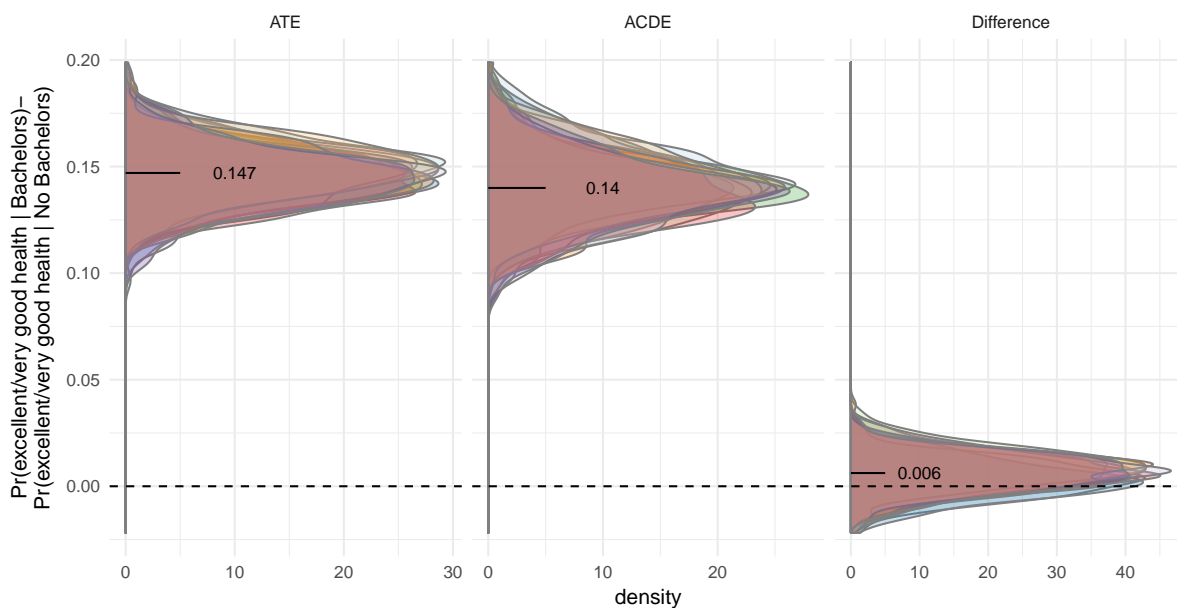


Figure 2.3: ATE, ACDE (at median income), and ATE-ACDE for Whites, excellent/very good health. Estimates from each imputed dataset are plotted as separate distributions. Average estimates, combined across imputations, are marked by solid line segments.

income pathways that tie education to health), or as both. Either way, breaking the association among education and income, by fixing income to its median, leads to a significant decrease in education's effect on health.

In contrast, Figure 2.3 shows that fixing income at its median level (approximately \$30k) is less impactful among Whites. The ATE among Whites is approximately 0.15. Controlling for income by setting it to its median reduces this effect to about 0.14, or by about 4%. These results suggest that income either does not play a large role as an indirect effect among Whites or—more likely—that an interactive effect exists, such that the direct effect of education on health is not especially dependent on income among Whites with average earnings.

The final set of results, presented in Figure 2.4, shows how the ACDE—and hence the

ATE-ACDE—varies when fixing M to different levels of income:

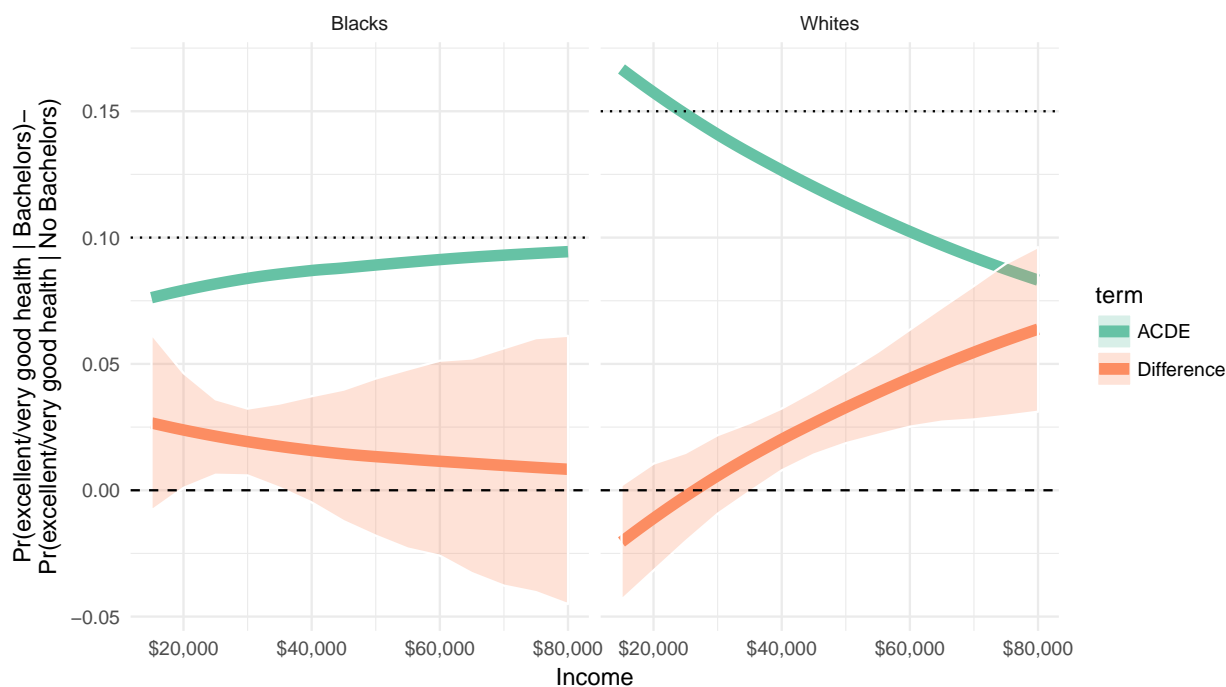


Figure 2.4: ACDE and ATE-ACDE for excellent/very good health, across values of income. ATE marked by dotted lines. 90% uncertainty intervals marked for ATE-ACDE estimates.

Figure 2.4 shows that a negative association exist among income and the direct effect of education for Whites. At lower levels of income, the ATE and ACDE are indistinguishable; when income is fixed to to be \$25k, for instance, less than 1% of the ATE is attenuated. At higher incomes, however, controlling for income is much more consequential. At \$80k, for example, nearly half (i.e., ATE = .15; ACDE = .08) of the effect of education on health is due—either as an indirect effect or interactive effect—to income. This pattern, of decreasing ACDE per increased income, suggests that income participates more as a mechanism of education’s effect on self-rated health among higher income individuals. That is, income either crowds out the influence of alternative mechanisms that link edu-

cation to health as it increases, individuals with higher incomes are more readily able to activate the alternative resources that tie education to health or both.

Figure 2.4 also shows that a, far weaker, positive association exist among income and the direct effect of education among Blacks. Among lower income individuals, the consequences of controlling for income are the largest. When income is controlled for at \$20k, the ATE is approximately 0.10, the ACDE is .025, and the percent decrease between the two is 25%. Income's influence diminishes quickly, however, with the ACDE approaching the ATE as income increases; by \$80k, controlling for income does little to diminish the effect of education on health. This pattern is the converse of Whites; among Blacks, income's role as a mechanism decreases as income increases. Alternative pathways that link education to health appear to take precedent at higher levels of income.

2.7 Discussion

This study adds to an expansive literature on racial variation in the association among education and health, by not only *quantifying the size* of racial differences in education's effect on health but, by *unpacking the process* that gives rise to these heterogeneous outcomes. Using sequential g-estimation and Add health, I estimate how the health status benefits of attaining a college degree depend on the earnings returned from education. I find that income diverges, markedly, across Blacks and Whites, in how it participates as a mechanism of education's health effect.

Among Whites, income appears to play a significant role as an interactive effect. At its median, which can approximate an indirect effect, income appears to play little to no role in creating health effects among Whites. As income increases, however, so does the proportion of education's total effect that is due, in some way, to income. While there are a number of interpretations for this behavior, one of the most plausible is that income serves to enhance the direct effect of education among Whites. That is, for Whites, higher income individuals are more readily able to active the alternative resources that tie education to health, to generate a health effect (e.g., marital status; mastery). This positive

interaction appears to be relatively unbound, with increasing income further enhancing the strength the pathways tie education to health.

Among Blacks, the opposite is implied. The, assumed, indirect effect of education on health through income is relatively large and significant; yet, as income increases, income's role in generating education's health effect washes away. A plausible reading of this behavior is that income participates mainly as an indirect effect among Blacks—e.g., that the income returned from education directly improves health—and less as an interactive effect—e.g., that increasing income does little to enhance the alternative pathways that link education to health. The weak, negative interaction between the ACDE and income suggests that income plays little to no role—as an indirect effect or direct effect—among individuals with incomes that are more common among college degree holders.

These results have, somewhat complex, implications for those interested in reducing disparities in educational gradients. Among individuals with lower earnings for college degree holders, income appears to play little to no role in creating racial disparities in education's effect. In fact, because Black individuals are more reliant on earnings to generate a health effect at these levels of income, removing the earnings boost that comes with educational attainment serves to widen disparities. In contrast, among individuals with incomes that typify college degree holders, earnings appear to be an important determinant of racial inequality in effect size. When income reaches \$50k, for instance, the ACDE for Blacks and Whites both approach 0.10. This results suggests that the additional health benefits of education experienced by Whites are attributable to income.

Despite this, our findings also suggest that simple interventions—which only address inequality in access to income—might not serve to equalize gradients. That is, our results show that income is bound in how important it can be in generating educational effects among Blacks. At levels of income that are more typical among college graduates, the association among education and health is largely agnostic to income. Changes in gradients among Blacks—and therefore changes in disparities—thus cannot be achieved by offering all individuals, *ceteris paribus*, the same, sizable, income returns to education.

Instead, interventions that seek to expand the role that income plays in creating gradients among Blacks might offer a way forward. For instance, efforts to reduce differences in purchasing power—e.g., reducing systematic racial barriers in leveraging income towards residence in salubrious neighborhoods—may allow for higher incomes to be more impactful in generating educational health effects among Blacks, and thus allow for interventions that reduce inequity in access to earnings to be more consequential. Research that clarifies why income, particularly when high, is limited in how it propagates educational gradients among Blacks is needed. Additional research that investigates why income plays a larger role among low income Blacks than low income Whites would prove productive as well.

Our findings have broader implications too, for understanding social inequality in health processes more generally. That is, heterogeneity exists in many of the health patterns that we observe in population health; how much any social input matters to health, typically, varies by one's social location (e.g., Bauldry 2015; Hudson et. al. 2012; Umberson and Montez 2011). Often, we make assumptions about how these processes are constituted, and forgo empirical examinations of why they diverge across subpopulations (Bowleg 2012; Pearson 2008). A common type of assumption implicitly made here is that *the structure of the process* that generates health per a given social input is *largely identical* across social groups and, consequentially, that inequality in total effect size is a product of restricted access to similar positive pathways (Pearson 2008).³ Our results demonstrate that this is not always the case. Indeed, our findings suggest that Black and White individuals take distinct *approaches* towards leveraging education to protect their health; the underlying process that generates better health per increased education varies by race such that, even at the same level of income, Blacks and Whites appear to differ in what resources they use to render good health from educational attainment. This results sug-

³In terms of this paper, that assumption might be that income behaves similarly in how it participates as a mechanism of education's health effect and, consequentially, that inequality in education's effect is due solely to differential access to income

gest that unequal outcomes may be generated by complex differences in how underlying processes are structured. Empirical work that unpacks how individuals of different social groups vary in how they utilize social inputs to protect health is encouraged, as it may further flesh out our understanding of how health outcomes and health inequalities come to be.

Our study is not without limitations. For one, while Add Health offers a number of advantages, the age range represented in these data is restricted. Educational effects, and income's role in generating them, likely vary across the life course in a way that our sample cannot capture. (Note that exploratory work with older cohorts, using the National Longitudinal Survey of Youth 1979 (Bureau of Labor Statistics 2012), yields similar results). As additional data-sources become available (e.g., *High School and Beyond: Midlife Follow Up*) (Warren et. al. 2017), this study should be repeated across age groups to examine how broadly our findings apply. Similarly, this study should be repeated for additional health outcomes, that become more stratified as individuals age. For another, our study takes a relatively static approach to defining race. While relying on broad racial categories is helpful, it does average over heterogeneous experiences that exist *within* these groups (e.g., Black women face very different experiences than Black men (Collins 1990); lighter skin-tone Blacks have very different experiences than darker skin-tone Blacks (Monk 2014)). Additional work that examines how other social features alter the patterns presented above would be productive. Lastly, by using a parametric modeling procedure, our study is subject to to the same model misspecification risks inherit to other parametric modeling strategies (e.g., Hill 2011). Additional work that takes advantage of (in-development) nonparametric sequential g-estimation strategies—particularly Ratkovic and Tingley (2017)'s *direct estimation* technique—would likely enhance inferences.

Data note

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Chapter 3

INEQUALITY IN EFFECT: DESCRIBING BLACK-WHITE HETEROGENEITY IN THE HEALTH-PROTECTIVE EFFECTS OF HIGHER EDUCATION

3.1 Abstract

Extensive literature documents Black-White disparities in the association among education and health. As informative as this work has been, there is room for additional analysis on the matter. Prior research has often only compared subpopulations along unidimensional, central tendency measures. While characterizing groups with averages provides a general understanding of how race, education, and health intersect, only doing so obscures breadth that exist within racial-groups, as well as alternative dimensions of the education health-relationship along which racial groups might differ. To help develop foundations about the interaction among race, education, and health in the US, I compare Blacks and Whites in terms of the effect that attaining a college degree has on self-rated health. In addition to describing racial differences in average effects, I compare: (1) how variable the health-returns to a college degree are within both groups, and (2) which members of each group experience the greatest health-benefits from completing a college degree. I use feature rich data from the National Longitudinal Study of Adolescent to Adult Health and an adaptation of Bayesian Additive Regression Trees in this endeavor. Results show that between racial-group inequality in educational gradients is complex and exist along multiple dimensions

3.2 Introduction

In the contemporary United States (US)—as well as many other historical and geographic contexts—educational attainment is a key associate of well-being (Hayward et. al. 2015; Montez and Friedman 2015). Individuals with higher levels of education fare better, than their less educated counterparts, on a mixture of economic (e.g., income; occupational prestige); human-capital (e.g., cognitive functioning; feeling of control over one’s own life); and social/psychosocial (e.g., marriage opportunities; exposure to discriminatory treatment) outcomes (Mirowsky and Ross 2003). These *educational gradients* in well-being have become reinforced over time, with the gap between college and non-college degree holders being wider now, more than “ever in the modern era” (Pew Research Center 2014).

The systematic association among education and social welfare is of special importance in population health. Many of the markers of well-being that are enhanced by educational attainment act as direct inputs to health; indeed, by governing access to an array of salubrious resources and experiences, one’s level of education dictates one’s ability to achieve and maintain good health (Phelan et. al. 2010). Educational gradients in health characterize the US population, such that individuals who possess at least a college degree typically experience lower mortality risk and better general health status (e.g., Hummer and Hernandez 2013); fewer functional limitations (e.g., Freedman and Martin 1999); decreased risk of developing various chronic and progressive conditions (e.g., Sharp and Gatz 2012; Vargas et. al. 2000); and increased psychological and emotional functioning (e.g., Bauldry 2015). Similar to educational gradients in welfare more generally, the health advantage held by more highly educated individuals has existed in the US for decades and become more acute over time (Masters et. al. 2012). Given education’s persistent, and expanding, role in shaping population health in the US, research which further parses this process is at a premium (Montez and Friedman 2015).

In efforts to catalog how education shapes health, population scientists have examined how educational gradients vary across US subpopulations (Walsemann et. al. 2013).

Researchers have recognized that the association among education and health does not exist within a vacuum, but rather is a complex social process embedded within, and thus contingent upon, the structural features/systems of power that characterize a population more generally (Hayward et. al. 2015; Montez and Friedman 2015). Perhaps the most consistent empirical finding from this subsection of the literature—which has shown that various markers of one’s social location modify the association among education and health—is that Non-Hispanic Blacks (Blacks) experience shallower health-returns to education than do Non-Hispanic Whites (Whites) (Crimmins and Saito 2001; Farmer and Ferraro 2005; Hayward et. al. 2000; Hayward et. al. 2015; Hummer and Hernandez 2013; Kimbro et. al. 2008; Liu and Hummer 2008; Masters et. al. 2012; Montez et. al. 2012; Shuey and Wilson 2008; Walsemann et. al. 2013). While the exact size of this disparity varies rather dramatically across studies—from findings which suggest that Blacks receive little to no health returns to education while Whites receive large and significant returns (e.g., Farmer and Ferraro 2005); to findings which suggest smaller, but measurable, Black-White inequity (e.g., Shuey and Wilson 2008)—research consistently shows that the gap in health between college educated Blacks and non-college educated Blacks is narrower than the difference in health between college educated Whites and their same-race, non-college educated peers.

As informative as studies of racial variation in education’s health effect have been, there is still room for additional analysis on the matter. In particular, prior research has often only compared subpopulations along unidimensional, central tendency measures (like the mean). While characterizing groups with averages provides a general understanding of how race, education, and health intersect in the US, *only* doing so obscures the breadth of experiences that exist *within racial-groups*, and thus alternative dimensions of the education health-relationship along which racial groups might differ (Sasson 2016). Fleshing out our descriptions of race-specific educational gradients with multi-dimensional summaries would add precision to our foundational understanding of how education acts to improve health among different racial subpopulations, our comprehen-

sion of how inequality manifest between groups—and consequentially, our ability to elaborate on how the education-health process interacts with the broader societal parameters under which it exists. (To expand on a quote from Montez et. al. (2012), “a theoretical explanation of the association [among education and health], *and the inequalities within it*, hinges on our ability to empirically describe it.”)

In this project, to help develop foundations about the interaction among race, education, and health in the US, I compare Black and White subpopulations in terms of the effect that attaining a college degree has on self-rated health. In addition to describing racial differences in *average effects*, I compare: (1) how variable the health-returns to a college degree are *within* both groups; as well as (2) *which members* of each group experience the greatest health-improvements from completing a college degree. For this analysis, I use feature rich data from the National Longitudinal Study of Adolescent to Adult Health (Harris et. al. 2009) and an adaptation of Bayesian Additive Regression Trees (Chipman et. al. 2010) for response surface modeling of heterogeneous treatment effects (Green and Kern 2012; Hill 2011). This combination of rich data and flexible modeling procedure allows for me to produce detailed and accurate descriptions of the quantities that I am interested in providing.

The remainder of this paper is organized as follows: the immediate-next section discuss the utility of summarizing and comparing racial groups along multiple-dimensions, other than just average effects. The section following that describes the methods and data, their value for this analysis, and the analytical strategy that will be used to produce results. The final sections present the results of the analysis and a discussion that contextualizes them in the broader population health literature.

3.3 Background

Though racial categories, like *black* and *white*, are useful summaries of one’s racial experience in the US, a robust literature documents that substantial variation exists in how individuals sorted into these groups are processed by the structures under which they ex-

ist (Collins 2000). Indeed, race intersects with other dimensions of one's social location—such as one's gender, region of birth, and nativity status—to produce multiplicative social experiences that cannot, entirely, be reduced to the sum of the components that constitute them (Bowleg 2012). How race factors into outcomes like access to income (e.g., Avent-Holt and Tomaskovic-Devey 2014); occupational experiences (e.g., Acker 2006; Wingfield 2013); exposure to specific regimes of cultural-racism (e.g., Acharya et. al. 2016) and structural-racism (e.g., Glenn 2002); access to housing (e.g., Friedman and Rosenbaum 2007); and access to marriage markets (e.g., Crowder and Tolnay 2000) is highly contingent upon the arrangement of an individual's other traits. Along some attributes (e.g., skin-tone) and on some outcomes (e.g., educational outcomes; health) even, within racial-group differences can match or exceed between-group differences (Monk 2014; Monk 2015). As many of the features that participate in education's health effect (e.g., income; occupation; marital outcomes; education and health themselves) vary markedly within racial groups, based on the arrangement of additional social attributes, one might expect for similar within-racial group heterogeneity to manifest in educational gradients in health (Bauer 2014).

To further elaborate on how race and education combine to affect health in the US, empirical efforts that recognize this higher-order, intersectional complexity are needed (Brown and Hargrove 2013; Bowleg 2012; Pearson 2008). Indeed, when thinking about how race comes to bear in population health processes—like the relationship among education and health—we are implicitly interested in describing how different *populations* experience a social determinant. In only using averages to characterize racial categories, we are in effect collapsing large and heterogeneous populations into single experiences. While average experiences are certainly important to capture—in that they often reflect the most common way that a health process manifest among a group—describing a population with *only* its average can overlook breadth and nuance in how a social determinant functions within a group (Brown et. al. 2016; Bowleg 2012; Sasson 2016); indeed, how a health-process manifest among a population likely inherits the underlying complexity

of the population it operates on. A holistic understanding of how education operates as a social determinant among a given racial group necessitates examining how this health process varies across members of said racial category (Monk 2015).

For the purposes of this paper, it is important to note that describing *within racial-group heterogeneity* in educational gradients informs our understanding of *between racial-group inequality* in educational gradients. In only comparing racial groups along mean returns to education, we are constrained to describing how racial groups are dissimilar in terms of average-magnitude; whether groups differ along other salient attributes of the education-health process is left obscured here. Indeed, features of the educational gradient that have been examined in other settings—such as how diffuse educational effects are within a population (or how certain it is that if an individual of a group attains a degree, that they will be able to achieve a certain level of health) (e.g., Sasson 2016); or which precollege attributes enhance/limit the salubrious effects of attaining a college degree (e.g., Bauldry 2014)—may vary dramatically between racial groups, and point to distinct inequalities that are missed in comparisons of singular, central tendency measures (Sasson 2016). To capture more comprehensive racial differences in how education functions to protect health, descriptions—and comparisons—of groups that go beyond central tendency magnitude are needed.

Similarly, given that *black-white* disparities are—like the categories that comprise them—neither fixed or essential, but rather vary in magnitude according to additional background traits (Monk 2015), examining within-group heterogeneity is useful for understanding the magnitude of racial inequality in education's health effect. Indeed, while differences in average-magnitudes quantify a common type of Black-White inequity, the size of said disparity is not guaranteed to be constant across individuals of different background attributes or across samples of different compositions (Xie 2013). (Black-White inequality may be larger among individuals with parents with college degrees than among individuals with parents with only high school degrees, for instance.) Describing within-group heterogeneity is informative in that it allows us to identify combinations of back-

ground traits where racial inequality in educational gradients are widest—and perhaps potential points of intervention for effectively narrowing racial disparities in educational gradients overall. Recasting *black-white* inequality as a parameter that varies interacts with additional traits and varies across the population can expand our ability to theorize about where and how inequality develops between groups (Monk 2015) and generally adds precision to our estimates of the magnitude of between-group differences (Xie 2013).

In sum, to develop our understanding of how race, education, and health interact in the US, more thorough descriptions of how this health process manifest among racial subpopulations are needed. To this end, I compare Black and White sample populations in terms of: (1) the average effect that education has on health; (2) how variable health returns are within both groups; and (3) which members of each population experience the greatest health-benefits from completing a college degree. By summarizing and comparing groups along multiple dimensions, particularly those that describe variation within-groups, I aim to add precision to our understanding of how race and racial inequality come to bear in educational gradients in health.

3.4 Methods

Analytical Framework

To fix ideas, the simple diagram presented in Figure 3.1 displays the relationship between education and health, and the *confounders*—i.e., features that: (1) occur prior to educational attainment; (2) occur prior to the health outcome being analyzed; and (3) jointly influence both—that surround it. Note that because I am interested in describing how education *acts as a social determinant of health* (rather than as an associate of health), I take special care in attempting to isolate $A \rightarrow Y$ from the multitude of confounders that might alternatively be driving it (Harper and Strumpf 2012; Lynch and Von Hippel 2016; Lleras-Muney 2005; Montez and Friedman 2015; Warren 2009).

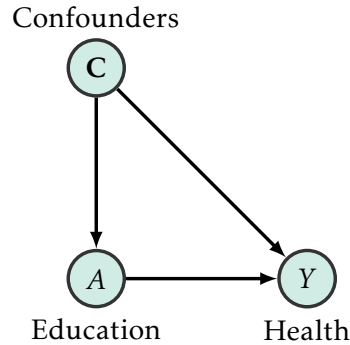


Figure 3.1: Conceptual model of how education and health are related.

To approximate a college degree’s effect on health, I estimate, for each racial group, the *average treatment effect of education on the treated* (i.e., ATT):

$$\text{ATT}(a, a') = \frac{1}{N_t} \sum_{i:A_i=1} Y_i(a) - Y_i(a') \quad (3.1)$$

The $\text{ATT}(a, a')$ gives a difference in counterfactual states (Rubin 2005). $Y_i(a)$ gives the health (Y) of an individual who was observed to have received a college degree ($A = a$), and $Y_i(a')$ gives the health of the *same* individual—with the same background traits (C_i)—had only they not received a college degree ($A = a'$). The average difference of $Y_i(a)$ and $Y_i(a')$, across all N_t individuals who were observed to have completed a college degree, summarizes the average effect that attaining a college degree has on health. Note that a more well-defined set of pre-education features (generally) increases one’s ability to isolate an “effect of interest” (Hill 2011). I compare ATTs across racial groups to describe how education’s average effect on health varies across groups.

To characterize the amount of within racial-group variation in education’s health effect, I estimate an *individual level educational effect*, or:

$$\tau(a, a')_i = Y_i(a) - Y_i(a'), \quad (3.2)$$

for each individual who completed a college degree in the data. If identified with a relatively flexible model, each $Y_i(a) - Y_i(a')$ is dependent on the vector of background traits (C_i) used to estimate it. As such, a more diffuse distribution of $\tau(a, a')$ across a population suggests greater effect variability among said population.

Through individual level educational effects provide a useful summary of variation in education's health effect, they are—due to the dimensionality of the vector of background traits that they are conditioned on—often too unstable to do more than describe our sample populations (Hill 2011). Additional technology is needed to assess which specific background features *systematically* generate educational effect heterogeneity among a group (Green and Kern 2012; Hill 2011). For this purpose, I estimate *conditional average treatment effects of a college degree on the treated* (i.e., CATT):

$$\text{CATT}(a, a', x) = \frac{1}{N_t} \sum_{i:A_i=1} (Y_i(a) - Y_i(a') | X_i = x) \quad (3.3)$$

Like the $\text{ATT}(a, a')$, the $\text{CATT}(a, a', x)$ summarizes the health effect of attaining a college degree. The primary difference here is that $\text{CATT}(a, a', x)$ fixes a particular background trait (X) to be equal across counterfactual scenarios. In terms of this paper, the CATT can be thought of as an estimate of education's average health effect, conditional on having background trait $X = x$. Assessing CATTs at various background attributes allows us to assess which features are more/less important for driving systematic heterogeneity in education's health effect among a population (Green and Kern 2012).

Statistical Model: Bayesian Additive Regression Trees

To estimate the quantities needed for this analysis, I use Bayesian Additive Regression Trees (BART) (Chipman et. al. 2010). BART is a nonparametric statistical learning algorithm defined by two components: (1) a sum-of-trees model; and (2) a Bayesian regularization prior. The sum-of-trees model is a collection of very low-dimensional, weak-learning regression-tree models that, when taken together, provide an exceptionally flexible model representation of the data. (Important interactions and other non-linearities

are easily captured in this component. Similarly, variables that do not contain much predictive power are easily identified and seldom used) (Hill 2011). The regularization prior, over each parameter of the sum-of-trees model, works to constrain the ensemble of regression trees and avoid overfitting (or misinterpreting noise in the data as meaningful associations). (See Chipman et. al. (2010) for a more technical description of this statistical algorithm.)

BART's *data driven* approach to modeling sample populations makes it ideal for this analysis. The combination of flexible model structure and restrictive prior allows BART to produce representations of the data that strike a principled balance between accuracy and parsimony (even in high dimensions). Because identifying quantities like the CATT often necessitates working with a sizable amount of confounders—many of which an author has little to no way of knowing how to properly specify in a model—BART and similar techniques are strongly recommend for the identification of causal effects (Dorie et. al. 2018; Green and Kern 2012; Hill 2011). Indeed, that BART allows the data itself to decide upon how it should be specified means that it can uncover systematic patterns in the data—such as which, and how much, background features modify the relationship among education and health—that might otherwise be missed or misrepresented in more ad-hoc model-specification searches (Hill 2011). BART has been shown to outperform traditional parametric models (e.g., linear regression) and alternative approaches to identification (e.g., matching; propensity score strategies) in the estimation of casual quantities of interest, particularly when treatment effects are assumed to heterogeneous among a population (Dorie et. al. 2018; Hill 2011; Hill et. al. 2011).

All quantities of interested are simulated from BART models of a health outcome regressed on a marker of education and a set of confounders—i.e., $Y \sim f_{\text{bart}}(A, \mathbf{C})$. To identify the $\text{ATT}(a, a')$, I estimate $E[Y|A = a, \mathbf{C}] - E[Y|A = a', \mathbf{C}]$ from draws of BART's posterior distribution (Hill 2011). Similarly, to identify $\tau(a, a')_i$, I simulate each individual's health, had they and had they not completed a college degree, and calculate and store the difference. To identify $\text{CATT}(a, a', x)$ quantities, I use the methodology described in Green and

Kern (2012), which involves simulating average treatment effects on synthetic versions of the data, where the background characteristic of interest (X) is held constant for all individuals. All models are estimated using Kapelner and Bleich’s (2016) `bartMachine` package in R (R Core Team 2018).

3.5 Data

Dataset: The National Longitudinal Study of Adolescent to Adult Health

Data for this project come from the National Longitudinal Study of Adolescent to Adult Health (Add Health). Add Health is an ongoing, nationally-representative, school-based study of adolescents in grades 7 to 12 that began in 1994 (Harris et. al. 2009). Add Health currently includes four waves of data: Waves 1 (W1: 1994-95); 2 (W2: 1996); 3 (W3: 2001-02); 4 (W4: 2007-08). In W4, respondents ranged in age from 24-32 years old.

For this paper, the utility of Add Health come primarily from their richness. Add Health is unique in terms of the range and diversity of variables it contains. At each wave, Add Health collected hundreds of detailed measures of individuals’ social, economic, psychological, and health states. The abundance of Add Health’s measures allows me to represent all components of Fig. 1—particularly the set of background features C —accurately and in detail. The relatively large sample of Black, White and college educated individuals contained in these data also make them ideal for this analysis. Add Health—and similar variable-rich surveys of young adults to adults—has been invaluable in addressing nuanced questions about education’s relationship with health (e.g., Bauldry 2014; Lynch and von Hippel 2016).

Measurement

To operationalize the components of Fig. 1, I divide Add Health into distinct time periods. The time-segment after W1 and before W4 is taken as a treatment period, where individuals are “assigned” an education level. Fixing this time period helps define all other periods: features that occurred prior to or during W1 can be considered pre-treatment (and thus a source of C), while features that occur at W4 can be considered post-treatment

(and thus a source of Y). Below, I describe the variables used to source these sets.

Education (A)

I define education according to whether an individual completed a college degree in the treatment period. Individuals who completed a college degree were assigned $A = 1$, while individuals who completed, at most, a high school degree were assigned $A = 0$. Respondents who were still enrolled in school at W4 or who completed their educational attainment prior to W1 are dropped. The comparison being made in this analysis then is explicitly *high school degree holders vs college degree holders*.

Health (Y)

Health is measured as W4 self-rated health status. Respondents were asked to describe their health as either *excellent, very good, good, fair, or poor*. Like many other researchers who use this measure (e.g., Braveman and Gottlieb 2014), I group adjacent categories to represent broad regions of health: excellent/very good health vs other, and fair/poor vs other. I choose this outcome: (1) given the measurable racial differences that exist in its association with education (e.g., Farmer and Ferraro 2005); (2) given its correlation with other outcomes for which racial heterogeneity exists in educational gradients (e.g., mortality) (Idler and Benyamini 1997); and (3) because it has been shown to share a causal relationship with college completion among the age group represented in Add Health (e.g., Lynch and von Hippel 2016). Note that, because analysis for excellent/very good health vs. other and fair/poor vs. other lead to the same substantive conclusions, I only present models for excellent/very good health vs. other in this paper. (Note also that *excellent/very good health*, and *superlative health* will be used interchangeably from here on.)

Pretreatment Confounders (C)

Pretreatment confounders (C) are variables that potentially influence one's probability of college completion and one's W4 health. Given the flexibility and discernment

of BART, as well as the desire to build as robust as set of pretreatment confounders as possible, I choose a broad mixture of features—representing a number of economic; demographic; social; educational; cognitive/meta-cognitive; health; behavioral; and adverse experience-related domains—for this vector. Specifically, I choose to define this set with: *self-identified sex category; age; skin-tone; nativity status; W1 language spoken at home; W1 depressive symptomatology; W1 self-rated health; W1 attractiveness; W1 days of school missed due to sick days; W1 hours slept a night; W1 times suspended from school; parental education; W1 number of parent’s in the household; parent nativity status; W1 parent receiving social support; W1 impulsiveness; W1 self-esteem; W1 how often upset by difficult problems; W1 drinking behavior; W1 engagement in violent delinquency (fights); W1 engagement in non-violent delinquency (property damage); W1 college expectations; if ever arrested before 18th birthday; W1 perceived social support, from parents; W1 perceived social support, from teachers; W1 age-standardized Peabody Picture-Vocabulary Test score; W1 grade in math class; W1 grade in English class; count of Adverse Child Experiences, sexual abuse; count of Adverse Child Experiences, physical abuse; W1 block-group median income; W1 block-group percent of adults with a college degree; W1 urban-rural classification; W1 lives in South; W1 perceived discrimination at school; W1 percent of teachers with a Master’s degrees at school; W1 average class size of school; and W1 if enrolled in public or private school.* Note that a more complete description of these variables can be found in the appendix.

Missing Data

Most variables used in the analysis are missing only a trivial amount (less than 3-percent) of data. Skin-tone—because it was collected at W3 where not all respondents were interviewed—is missing the most, with approximately 15% of all cases missing data. To retain subjects, and avoid the bias that comes with listwise deletion, I utilize the “imputation” procedure outlined in Kapelner and Bleich (2015). (In sum, this process incorporates missingness into the tree-building process of BART). Models that include and exclude cases with missing values produce similar substantive results.

3.6 Results

To contextualize our samples, Tables 1 and 2 provide descriptives statistics for a select number of variables.

Table 3.1: Summary statistics: Blacks

feature	high school ($n = 664$)		college ($n = 522$)	
	mean/freq.	(sd)	mean/freq.	(sd)
w4 superlative SRH	0.52	(-)	0.61	(-)
w4 age	28.66	(1.89)	28.17	(1.8)
female	0.45	(-)	0.61	(-)
“light” skin-tone	0.08	(-)	0.16	(-)
US born	0.99	(-)	0.98	(-)
southern	0.67	(-)	0.56	(-)
w1 depression	6.87	(4.18)	5.08	(4.04)
(log) block income	9.90	(0.54)	10.1	(0.56)
two-parent household	0.43	(-)	0.58	(-)
arrested before 18	0.17	(-)	0.06	(-)
w1 impulsive (strong agree)	0.13	(-)	0.04	(-)
% teachers with masters	43.67	(22.93)	47.24	(26.74)
w1 picture-vocabulary score	88.76	(13.33)	100.93	(12.62)
ACEs: never physical abuse	0.86	(-)	0.86	(-)

In both Black ($n = 1,186$) and White ($n = 3,407$) samples, pretreatment confounders vary, as one would expect, with education status. Individuals who completed a college degree in the treatment period were more likely to identify as female, had higher standardized test scores, and had fewer depressive symptoms in W1 than individuals who

Table 3.2: Summary statistics: Whites

feature	high school ($n = 1,564$)		college ($n = 1,843$)	
	mean/freq.	(sd)	mean/freq.	(sd)
w4 superlative SRH	0.46	(-)	0.74	(-)
w4 age	28.62	(1.84)	28.23	(1.76)
female	0.44	(-)	0.56	(-)
“light” skin-tone	0.99	(-)	0.99	(-)
US born	0.99	(-)	0.99	(-)
southern	0.37	(-)	0.30	(-)
w1 depression	6.32	(4.37)	4.59	(3.7)
(log) block income	10.2	(0.38)	10.5	(0.38)
two-parent household	0.68	(-)	0.84	(-)
arrested before 18	0.16	(-)	0.06	(-)
w1 impulsive (strong agree)	0.12	(-)	0.04	(-)
% teachers with masters	49.33	(25.31)	60.0	(24.4)
w1 picture-vocabulary score	99.85	(11.79)	109.43	(10.72)
ACEs: never physical abuse	0.80	(-)	0.89	(-)

only attained a high-school degree. Among both racial groups, college educated individuals were also less likely to have assessed themselves as impulsive in W1 and to have experienced contact with the criminal justice system. Among Blacks, individuals who attained a college degree were more likely to be assessed as having “light” skin-tones, and less likely to be from the South. Among Whites, adverse childhood experiences and block-group SES appeared to differentiate treated and untreated subjects. Most individuals, regardless of race or education status, were born in the US and approximately 29 years old.

To begin to unpack how education shapes health among Blacks and among Whites, Figure 3.2 summarizes average health returns to a college degree among both groups (1) as observed in the data; and (2) as estimated conditional on the pretreatment confounders mentioned above.

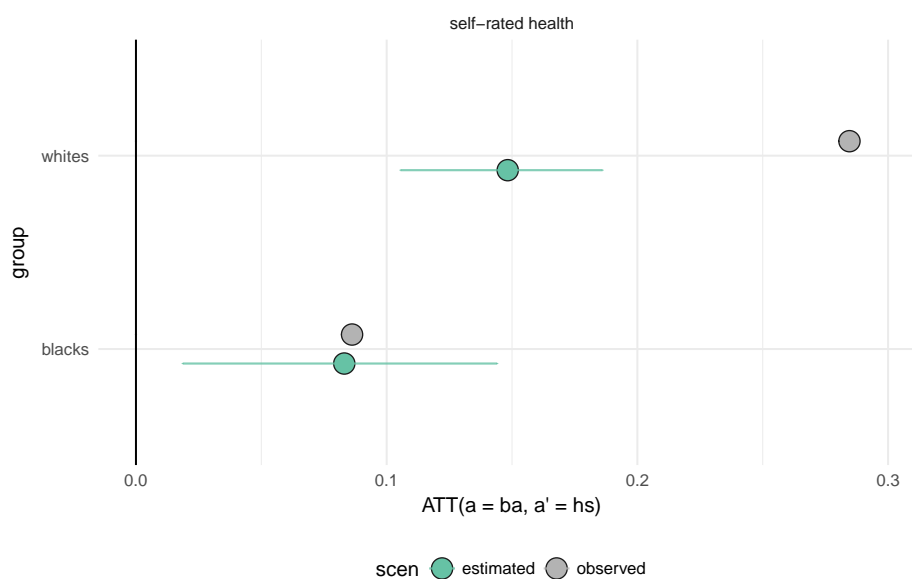


Figure 3.2: Observed and estimated average effect $[ATT(a, a')]$ of attaining a college degree on the probability of reporting *excellent/very good health*. 95% uncertainty marked.

Figure 3.2 displays education's average effect on excellent/very good self-rated health. When no confounders are accounted for, Blacks appear to benefit much less from completing a college degree than do Whites: the observed difference in the probability of reporting excellent/very good health between college and high-school educated Blacks is approximately 8.5 percentage points, while the same change in education among Whites yields a 30-point increase in the probability of superlative health. When comparing estimates that better account for selection processes, disparities in returns narrow considerably; where Blacks who attained a college degree are estimated to have experienced a 7.5 point increase in the probability of reporting excellent/very good health, the ATT for

Whites is 15-points. The ratio of White/Black effect sizes shrinks from approximately 3.2 in the observed case to 1.9 in the estimated case. That the effect size among Blacks remains consistent, but shrinks considerably among Whites, hints that the confounders listed above play differential roles as part of education’s health effect across racial groups.

To further interrogate how education shapes self-rated health in both racial groups—beyond the average effects given above—Figure 3.3 plots model-estimated educational effects for every college educated individual in the data (i.e., $\tau(a, a')_i$). I also scale these estimates by their groups-specific means (e.g., an estimate of 1.2 means that an individual’s estimated educational effect is 1.2 times greater than the average effect of their group).

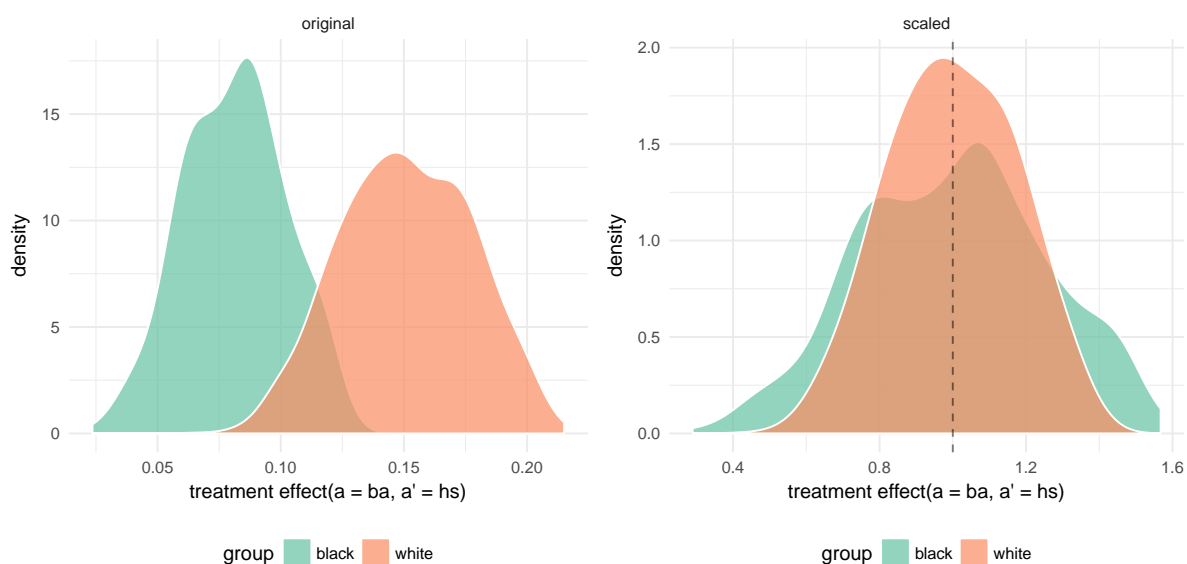


Figure 3.3: *Left*: Distribution of individual level educational effects $[\tau(a, a')_i]$ for excellent/very good self-rated health. *Right*: Mean-scaled $\tau(a, a')_i$ distributions.

Figure 3.3 shows that measurable within-group variability exists in how education functions as a social determinant of health among both sample populations. Depending on the arrangement of their pretreatment characteristics, 99% of Whites were estimated

to have experienced between a 9.5-point to 20-point increase in the probability of superlative health after completing a college degree (approximately 0.64 to 1.31 times the estimated average educational effect among Whites). As indicated by the heavier-tails in the mean-scaled distribution, a college degree's effect on self-rated health appears to be somewhat more dependent on an individual's background traits among Blacks. The bottom 1% of the Black sample were estimated to have only experienced a 3.1 point increase in the probability of superlative health after college, while the top 99%-percentile saw nearly a 13-point increase (approximately 0.42 to 1.6 times the estimated average educational effect). Figure 3.3 shows that while many individuals in both populations experienced average returns to education, many others did not—and that how education manifest as a social determinant of health is somewhat more dependent on one's background among Blacks than among Whites.

Note that our interpretation of Black-White inequality in educational gradients varies across the population. Among individuals with the weakest effects among both groups, Whites had returns that were 2.5 times the size of Blacks; among individuals who had the strongest health returns to college among both samples, Whites saw returns that were only 1.5 times greater than Blacks. As indicated by the overlapping density in the left-hand panel of Figure 3.3, certain Black individuals were estimated to have experienced greater returns than certain White individuals. Despite the wide breadth of effects within both groups, very few White individuals experienced returns that were lower than the average effect among Blacks. Indeed, Whites from most all combinations of background characteristics were able to achieve improvements from college that were *at least* that of the average Black individual. The White/Black ratio of effect sizes is 8/1 at its greatest and 0.50/1 at its least.

To investigate which background characteristics are systematically generating the heterogeneity on display in Figure 3.4, I calculate and plot conditional average educational values (i.e., $CATT(a, a', x)$) for multiple background characteristics. (Note that because BART is a black-box learner, that does not return an interpretable model structure, I cal-

culate CATTs for each pretreatment variable in the analysis.) Figure 3.4 displays results for the variables with the largest systematic influence on treatment effects.

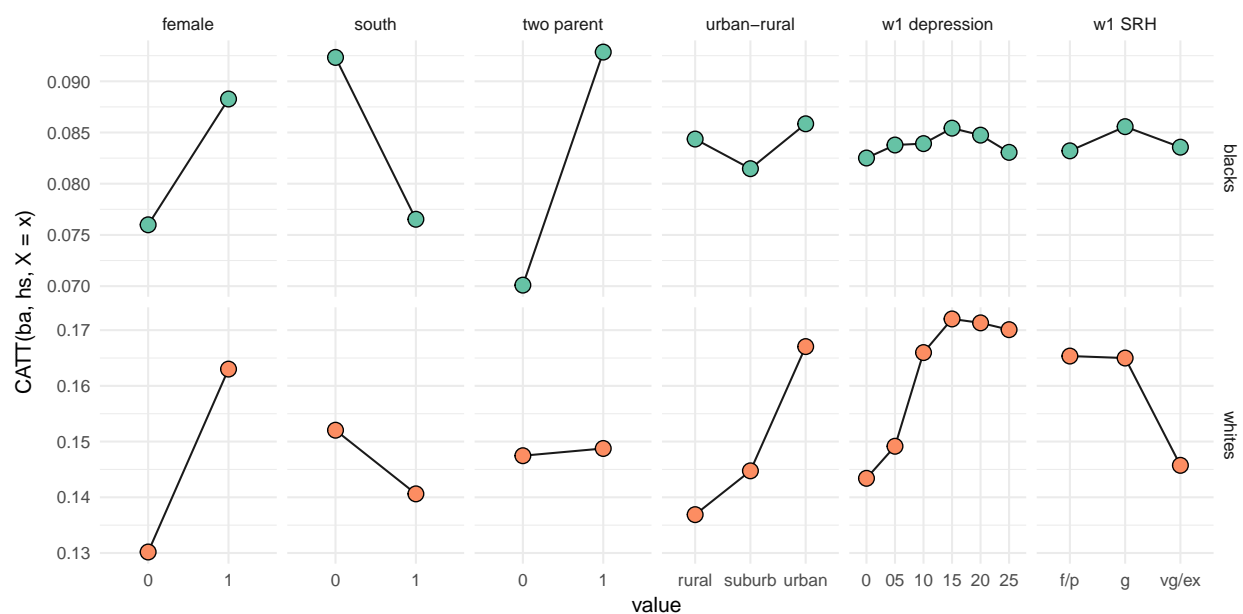


Figure 3.4: Select Conditional Average Treatment Effects [CATT(a, a', x)] for the probability of reporting very good or excellent self-rated health.

Figure 4 shows that which background traits modify education's relationship with self-rated health vary by race as well. Among Whites, individuals with poor health in adolescence experienced greater payoffs from attaining a college degree. Simply shifting the entire sample of Whites from a W1 CES-D depression score of 0 to a score of 15 increased average educational effects by 3-points. (Put differently, individuals who experienced high levels of depression in adolescence had average health returns to education that were about 20% higher than individuals who experienced low levels of depression). Individuals who were in *fair*, *poor*, or *good* self-rated health during adolescence similarly experienced greater health returns to education than individuals who with *excellent* or

very good health as a youth. Females (as compared to males) and individuals who grew up in urban settings (as compared to rural or suburban settings) also tended to experience greater health returns. Figure 4 suggests a general pattern, where White individuals who experienced structural marginalization or disadvantage prior to completing their education (e.g., women compared to men; individuals in worse health compare to individuals with greater health) benefited more from completing a college degree.

Among Blacks, educational effect heterogeneity appears to be driven mostly by one's region of residence during childhood, one's gender, and whether one lived in a two-parent household. Individuals who lived in the South, were male, and lived with a single parent experienced weaker returns to health (up to a 25% decrease, along any single trait) compared to their peers. In contrast to Whites—save for on gender—occupying a marginalized position prior to educational attainment did not positively modify education's effect on health. Blacks with poor health outcomes prior to college experienced no greater benefit to completing a college degree, and Blacks from the South—an area of the country with higher rates of an assortment of poor outcomes—and more marginalized household structures experienced weaker returns than their more privileged counterparts.

Informed by the patterns uncovered in Figure 4, exploratory searches of the response surface suggest that Black-White inequality fluctuated with these patterns in background traits as well. In CATT searches which fixed traits to represent a more advantaged pretreatment state—i.e., $CATT(a, a', x)$, where $x = \{\text{two parent household; not from the south; W1 depression score of 0; and excellent W1 self-rated health}\}$ —White/Black CATT estimates were of a ratio of 1.5 to 1 (14.5 points/9.5 points). In CATT estimates that fixed values to more marginalized pretreatment conditions—i.e., $x = \{\text{single parent household; from the south; W1 depression score of 10; and good W1 self-rated health}\}$ —Whites experienced an 17 point increase in the probability of superlative health, where Blacks experienced a 6 point increase (for a 2.8 times White/Black ratio). (Note that these ratios ap-

proach the largest White-return/largest Black return and weakest White-return/weakest Black-return ratios discussed alongside Figure 3.)

3.7 Discussion

This study adds depth to our understanding of racial variation in one of the most prominent processes in US population health—the relationship among education and health. To help foundation ideas of how race comes to bear in this process, I examine how a college degree acts to improve self-rated health among Blacks and among Whites along multiple dimensions; these include racial differences in average educational effects and racial differences in within-group education effect behavior. In these descriptions, I find that Black-White differences in educational gradients go beyond average inequality in magnitude. Indeed, I find several patterns that highlight that complex differences exist between groups in how education functions to protect health and motivate additional research.

Like other studies, I find that Whites experience greater average health returns to college than do Blacks. Notably, I find that controlling for a robust set of selection-related features shrinks educational effects considerably among Whites, but not among Blacks. This results suggests that a large portion of the health-advantage experienced by college educated Whites, over high school educated Whites, is not due to the benefits that education confers, but rather is reflective of health-advantage that would have been experienced whether a college degree was completed or not. The opposite is true among Blacks, where accounting for pretreatment conditions does little to reduce average educational effects. This behavior suggests that much of the health-status advantage that college-educated Blacks have over high-school educated Blacks is due explicitly to human capital/credentialism mechanisms—and thus represents a health advantage that would not be experienced otherwise. Still, even when accounting for many pretreatment confounders, average White effects were larger than average Black effects.

Beyond average effects, I find that Blacks and Whites vary in terms of within-group ef-

fect variability. Health returns are quite diffuse among both groups, but somewhat more so among Blacks. Indeed, whether a Black individual experienced a small improvement to health, that neared zero, or a large improvement, that neared average effects among Whites, was strongly dependent upon the intersection of their background characteristics. That the distribution of effects among Whites was somewhat more tightly packed around the mean, and largely bound above average effects among Blacks, suggests that the conditions require to experience a sizable health improvement from college were somewhat less specific among this group. That experiencing appreciable health returns to education is somewhat more dependent on one's background traits among Blacks than among Whites suggest a subtle form of inequality that is otherwise washed over by just comparing group means. That White effects, even at their most shallow, bound above average Black effects similarly adds depth to our understanding of inequality; these findings show that "in the worst case scenario" Whites are able to leverage education in ways that are similar to the average Black individual. Efforts that further analyze this inequality, and describe the structural reasons as to why Whites from a wider range of background traits are able to generate sizable health returns from college degrees would be productive.

Black and White populations also varied in *what features modified* the relationship among education and health. Among Whites, a general pattern emerged from the data such that more marginalized individuals experienced greater health returns to education. This pattern is consistent with a burgeoning set of studies on health status among the US population, which show that educational attainment can help wash over otherwise health-degrading, pre-college disadvantages (Montez et. al. 2014; Schafer et. al. 2014). The opposite pattern emerged among Blacks, with individuals who occupied more marginalized positions experiencing either benefits at or below their group-specific average. These results are consistent with an alternative set of studies, which show that education can serve to reinforce preexisting inequities, or that experiencing appreciable health returns to education is contingent upon occupying a advantageous position prior to

college (e.g., Bauldry 2014). The current study shows that these alternative modification schemes can exist within a population at the same time, and do not apply wholesale to every subgroup. Indeed, these results suggest that *how* education acts to improve health varies among members of the same, broad population. Additional research that unpacks why education serves as a potential mechanism of health-democratization among Whites, but, at worst, as a reinforcer of inequity among Blacks, would certainly prove productive.

The final set of results also showed that Black-White inequalities in education's health effect were not fixed and singular, but rather varied according to shared background traits. Black-White inequalities were narrowest among individuals from more privileged prior conditions and widest among individuals from more marginalized positions. Indeed, these results suggest that racial inequality in how education can be used to protect health intensifies with other forms of disadvantage. Paired with the above results, this pattern appears to be related to the fact that Whites are able to use a college degree to wash over pre-college health and health-related disadvantages, while the same compensatory structure is largely absent among Blacks. Further empirical work is needed to better understand the sources of this fluctuating inequality. The results provided here though suggest that making gains in narrowing Black-White inequity in educational gradients necessitates reducing exposure to more marginalized pre-college conditions among Blacks. Structural disadvantage experienced prior to education appears to play a meaningful in generating racial disparities in how education can be used to protect one's health.

This study is certainly not without limitations. First, though the scope placed on age, race, education, and health allow for precision in identifying quantities of interest, expansion of this project is needed. Future studies should examine similar quantities at different points in the life-course—where the association among education and health evolves and changes (Montez and Friedman 2015)—among different racial groups—who have markedly different social experiences than either Blacks or Whites (e.g., Williams et. al. 2016)—and at differential levels of education—where educational effects vary in

strength (e.g., Montez et. al. 2012)—to paint a more complete picture of how race comes to bear in educational gradients in self-rated health. Additional outcomes should similarly be examined to develop a more complete picture of racial variation in educational gradients. Second, although I do control for a robust vector of pretreatment covariates, there is no guarantee that this vector of traits represents all major confounders of the education-health association. (The effects of features like very early life conditions for example, which are not available in Add Health, may not be captured entirely in the vector of traits I modeled.) Without more complete data, experiments, or ideal instruments—all of which are largely absent in population health (and arguably in social science more generally) (Hill 2011)—it is difficult to make additional progress on this point (Harper and Strumpf 2012). As new data opportunities become available, work that re-examines the effect sizes presented here should be conducted. Finally, although I do search through treatment effect using patterns that emerge from the data, alternative searches, which are built from strong theoretical frameworks, would be useful. robust theories can help search through the massive parameter space that defines educational effects in this study and help uncover additional combinations of pretreatment features that drive heterogeneity in populations, as well as where inequality is most wide or most narrow.

Despite these limitations, this study demonstrates that how education functions as a determinant of health varies, in multifaceted ways, across racial subpopulations in the US. Like recent health research, from authors who have centered their analyses around within-group heterogeneity (e.g., Brown et. al. 2016; Monk 2015; Sasson 2016), I find that the education-health process inherits the complexity of the populations it operates on. As such, like other authors in this domain, I encourage researchers who are interested in cataloging disparities along *any salient social attribute* and in *any social determinant of health* to investigate within-group heterogeneity; capturing the broad and nuanced ways in which a social determinant manifest among a population adds depth and precision to our understanding of how said process manifest between populations. As has been stated in broader discussions of population health processes (e.g., Montez and Frideman 2015)

how social forces impact health is heterogeneous across time, place, and other conditions; centering this idea in *empirical* research efforts is needed to make progress in understanding how social conditions shape population health. I encourage researchers to embrace this idea and tackle it with the rich datasets and statistical tools that are available to us today.

Data note

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Chapter 4

INEQUALITY IN CONTEXT: NEIGHBORHOOD ENVIRONMENTS AND THE ASSOCIATION AMONG EDUCATION AND HEALTH

4.1 *Abstract*

The association among education and health—i.e., *the educational gradient in health*—is known to fluctuate, in strength, across subsections of the US population. Emergent literature suggests that educational gradients are particularly affected by contextual environments; higher-level features, like one's state of residence, have indeed been shown to modify *how much* attaining an advanced educational credential matters for one's health. To add resolution to this insight, this study examines how the *neighborhood environment*, an especially salient level of geographic-organization, impacts educational gradients in the US. Using data from the Chicago Community Adult Health Study ($n = 3,105$) and Bayesian multilevel logistic regression models, I examine how self-rated health disparities between college and non-college educated individuals grow/shrink in the presence of a neighborhood-level resource (i.e., access to quality resources) and with exposure to a neighborhood-level health challenge (i.e., exposure to physical hazards). Results suggests that how tightly coupled education is with one's well-being is strongly contingent upon one's immediate external-risks, but less so on one's access to neighborhood resources.

4.2 *Introduction*

Education organizes health in the United States (US). Among the general population, individuals with higher levels of educational attainment typically experience fewer progressive and chronic conditions (Vargas et. al. 2000; Zhang et. al. 2016); elevated levels of psychological and emotional-functioning (Bauldry 2014); and better general health-

status (Rogers et. al. 2000) than their less educated peers. Education's positive association with well-being has characterized the US for decades—despite shifts in health risks and technologies (Meara et. al. 2009)—become more conspicuous over time (Masters et. al. 2012) and, under specific conditions, been shown to be underpinned by a causal process (Lynch and Von Hippel 2016; Warren 2009). Taken together, education's multifaceted, sometimes causal, and increasingly intense association with health positions it as a key mechanism of health stratification in the US (Hayward et. al. 2015; Phelan et. al. 2010).

In parsing *educational gradients in health*—i.e., the patterns described above, of more highly educated individuals generally experiencing better health—researchers have uncovered an elaborate dependency structure. Indeed, a single, static educational gradient does not generalize across the US population; exactly *how much* one benefits from educational attainment is contingent upon the arrangement of their other social attributes (Walsemann et. al. 2013). (Social features like race (Kimbrow et. al. 2008), gender (Ross and Mirowsky 2006) and childhood socioeconomic status (Montez and Hayward 2014), for instance, have been shown to shape the extent to which one's health is improved from attaining additional educational credentials.) Cataloging how education interacts with other dimensions of the social world, to produce variable health outcomes, adds precision to our understanding of how education functions as a determinant of health more broadly; studies that describe heterogeneity in educational gradients, across groups of individuals defined by discrete social traits, foreground current research efforts as such (Bauldry 2014; Sasson 2016; Montez and Friedman 2015).

Among studies that document variable educational gradients across the US population, some of the most informative are those that clarify the role of context (Hayward et. al. 1997; Montez et. al. 2017; Montez and Berkman 2014). Researchers working in this area have, in somewhat different terms, posited that contextual environments are implicit in the process that underlies educational health effects. Indeed, education is theorized to participate in health by offering individuals a set of resources (e.g., additional income; steady employment; elevated feelings of control over one's own life) that can be used to

ward off multiple, external health challenges (Mirowsky and Ross 2003). If education protects health by *guarding* against otherwise health-damaging exposures, then how—and how much—education matters for health may be inextricably linked to the social, physical, and cultural contexts that individuals contend with.

An emergent set of empirical work—which shows that health disparities between high- and low-educated individuals vary across geographies—aligns with this framing. Montez et. al. (2017), for instance, show that the economic consequences of having low-levels of education vary from state-to-state, and that this variation in material conditions affects educational disparities in health. (States where low educational attainment is more tightly coupled with worse material conditions (e.g., higher poverty rates) display higher rates of disability among their low-education populations and thus wider educational disparities in health overall.) Similar context-induced variation in educational gradients has been observed across US regions (Montez and Berkman 2014) and urban-rural communities (Hayward et. al. 1997), as well as across European nations with varying welfare regimes (Cambois et. al. 2016). Taken altogether, this burgeoning empirical literature suggests that contextual settings shift how “education matters” (both socially and economically) and consequently how/why education matters for one’s health.

Educational gradients in health have indeed been shown to vary, in pronounced ways, across socially-defined environments in the US. As informative as the literature that has produced this insight has been, there is still room for additional analysis on how context comes to bear in educational gradients. To add resolution to this developing framework, research that examines how educational disparities in health vary along an (incredibly) salient level of geographic-organization—i.e., *the neighborhood*—is needed. Neighborhood environments represent among the most immediate, health-relevant, contextual spaces in which individuals operate and thus contextual profiles that individuals contend with on a daily basis. Describing how individuals of different levels of education experience the *same* neighborhood health risks—and, conversely, resources—is an important step in further understanding how context intersects with education to influence health.

In this paper, to help develop ideas of how context and education interact to produce health, I describe how self-rated health manifests among individuals of varying levels of education, across different neighborhood contexts. I specifically examine how health disparities between college educated and non-college educated individuals grow/shrink in the presence of a neighborhood level resource—i.e., *access to quality resources*—and with exposure to a neighborhood-level health challenge—i.e., *exposure to physical hazards*. I use data from the Chicago Community Adult Health Study (2001-2003) (House et. al. 2012) and Bayesian multilevel logistic regression models, with weakly informative priors (Gelman et. al. 2008), to estimate the quantities needed for this analysis.

The remainder of the paper is organized as follows: the immediate-next section briefly discusses how neighborhood contextual environments might interact with education to produce variable health risks among residents. The following sections discuss the data and methods used in this project. The final sections present the results of the analysis and offer a discussion that contextualizes them within the broader population health literature.

4.3 Background

Neighborhood environments are critical dimensions of space in the US. One's immediate spatial context shapes access to an array of social and institutional resources (e.g., social networks; socialization; access to private goods; access to public goods), as well as exposure to a number of negative social and environmental exposures (e.g., exposure to violence; exposure to toxins; stigmatization by out-of-neighborhood actors) (Galster 2012; Small and McDermott 2006; Sampson 2011). By directly organizing individuals' daily experiences, neighborhoods directly organize individuals' social welfare.

Among the markers of well-being that are associated with neighborhood environments, health is one of the most conspicuous (Diez Roux and Mair 2010). Residing in a neighborhood with elevated levels of social and institutional resources is theorized to be health-protective, as it offers collective, salubrious goods that can be accessed frequently

and (often) at little (or at least reduced) cost (Diez Roux 2001). Residing in neighborhoods with elevated levels of hazards is conversely damaging to well-being, as doing so means sustained exposure to health-eroding chronic stressors and other environmental toxins (Hajat et. al. 2013). Empirical evidence which demonstrates the salience of neighborhoods for health is extensive (if mixed at times); neighborhoods that are rich in resources and limited in hazards are typically characterized by residents with superlative general health-status and low morality risks (Mode et. al. 2016); few chronic and progressive conditions (Mujahid et. al. 2008; Clarke et. al. 2015); and elevated psychological functioning (Latkin and Curry 2003). The health profiles of residents of more marginalized neighborhoods—i.e., high risk/low resource spaces—often read in reverse.

For all of its virtues, knowledge of the link between neighborhood environments and the health of the individuals who inhabit them is still developing (Diez Roux and Mair 2010; Sharkey and Faber 2014). Much of the empirical work that describes how neighborhoods affect health treat individual-level characteristics as nuisance parameters to be averaged over. While this analytical strategy is useful in some ways—namely in that it helps to identify “average neighborhood effects”—it also obscures potentially important heterogeneity in how individuals experience the same neighborhood contexts (Sharkey and Faber 2014). Our understanding of how neighborhood environments modify certain individual-level processes, or for whom neighborhood-spaces are most consequential, is generally somewhat coarse.

Neighborhoods may play particularly profound roles in shaping how educational attainment impacts health among individuals. Indeed, like other dimensions of space mentioned above (e.g., states), neighborhood environments may shift how tightly coupled education is with material well-being. In neighborhood environments where high-quality, collective resources are abundant, for instance, the material consequences of not having advanced educational attainment may be trivial; individuals in these spaces may be able to rely on neighborhood-level social and institutional resources to effectively supplement well-being, regardless of their own personal circumstances. Put in terms

of health, educational gradients may be relatively shallow in environments with many neighborhood-level resources, as these alternative, contextual-level goods can be used as effective “stand-ins” for the protective resources/advantages that educational attainment would otherwise provide.

Similarly, educational disparities in health may become exacerbated in neighborhood spaces with high levels of negative exposures. As Montez et. al. (2017) argue in their exploration of states, *high education may provide a personal firewall to suboptimal context*. Individuals with high educational attainment may be able to use the protective resources that accompany their credentials to effectively resist the otherwise health-damaging exposures that often accompany more marginalized neighborhood spaces. Lacking these personal, education-borne resources, individuals with lower levels of educational attainment may be more subject to the ill-effects of neighborhood propagated health-challenges (Montez et. al. 2017). In neighborhood environments where daily exposure to health-challenges are high, education may indeed be an essential means of maintaining good health.

Neighborhood environments may, through their allocation of external risks and goods, help define educational health disparities the US. Given this potentially joint—potentially profound—effect on health, the present study examines how the association among education and health fluctuates along different neighborhood characteristics. In particular, I examine *if how much education matters for one’s health varies (1) among neighborhoods with different levels of physical hazards; and (2) among neighborhoods that vary in terms of access to high-quality institutions and organizations*. Among neighborhoods with varying levels of physical hazards, I predict that educational disparities in health will be most pronounced in spaces defined by high levels of hazards. (High-educated individuals in high-hazard areas should be able to leverage their education to ward-off external health-challenges better than their low-education counterparts.) Among neighborhoods with varying levels of quality institutions/organizations, I expect for educational disparities to be shallowest in spaces where quality resources abound. (When many external, salu-

brious neighborhood-resources are available to individuals, I expect for one's personal level of educational attainment to be less essential for maintaining good health.)

4.4 Data

The Chicago Community Adult Health Study

Data for this project come from the Chicago Community Adult Health Study (CCAHS) (House et. al. 2012). The CCAHS is comprised of a cross-sectional sample of 3,105 individuals, all over the age of 18, living in Chicago between 2001 and 2003. Interviewers collected information about each respondent's current social, economic, and demographic circumstances. In addition to collecting characteristics of individual respondents, researchers recorded detailed information on the 343 neighborhood-spaces that individuals inhabited. In these data, "neighborhoods" are defined as subsets of census-tracts that are geographically contiguous and socially similar. (Please see House et. al. (2012) and Sampson et. al. (1999) for further details on how these neighborhood spaces are defined.) Note that the 343 neighborhood-clusters in the data represent the *census* of neighborhood-clusters in the city of Chicago.

Measures

The focal individual-level predictor (A), *educational attainment*, is defined around whether a respondent held a college degree at the time of their interview. Individuals who answered *yes* to the question, *do you have a bachelor's degree from a four year college?* are coded as $A = 1$. Individuals who answered *no* are coded as $A = 0$. A college degree is chosen as the focal comparison point given that particularly substantial inequalities, health and otherwise, exists between individuals split across this level of educational attainment (Bauldry 2014; Pew Research Center 2015).

The response (Y)—*self-rated health*—is defined around a respondent's answer to the question, *all in all, would you say that your health is generally excellent, very good, good, fair, or poor?* Like many other researchers who use this measure (e.g., Braveman and Gottlieb

2014), I group adjacent categories to represent broad regions of health: *excellent/very good health vs other* and *fair/poor vs. other*. I choose this outcome (1) given its strong and consistent correlation with a spectrum of health measures that vary with education (e.g., mortality; recurring health problems; physical tiredness; stress; underlying biomarkers) (Bauldry 2014; Idler and Benyamini 1997; Jylha et. al. 2006; Jylha 2009); and (2) because it has been shown to share a causal relationship with college completion (e.g., Lynch and von Hippel 2016). (Note that because results for *excellent/very good health vs other* and *fair/poor health vs. other* lead to the same substitutive conclusions, I only present results for the former in this paper. Note also that I use *excellent/very good health* and *superlative health* interchangeably from here on.)

Neighborhood physical hazards (Z_1), the first of our neighborhood-level features of interest, is defined using a scale-measure in CCAHS. In the CCAHS questionnaire, each individual was asked a series of questions related to how hazardous they found their neighborhood-cluster; these include: (1) *Some neighborhoods have problems with air quality because of things like exhaust from cars, trucks, and buses; smoke from nearby industrial areas; or dust and dirt from trash or construction. How would you rate the quality of the air in this neighborhood?*; (2) *How dangerous do you think traffic is in your neighborhood either to people driving in cars or walking on the street?*; and (3) *Some neighborhoods are noisier places to live than others. Noise can come from people living nearby, people walking or hanging out on the street, traffic, or construction. How noisy would you say your neighborhood is?* Using these responses in conjunction with a multilevel Empirical-Bayes technique, CCAHS estimated a neighborhood-level physical hazard score for each neighborhood cluster. (Please see the CCAHS documentation (House et. al. 2010) for additional information on the estimation technique used to construct this measure.) Higher scores on this scale indicate more physically hazardous neighborhoods. Hazard scores range from approximately 2.1 (very low hazards) to 3.03 (very high hazards).

Neighborhood institutional/organizational resource quality (Z_2) is measured in a similar

way. Respondents were asked (1) *How would you rate the quality of the stores that serve this neighborhood, such as local grocery stores or drug stores;* and (2) *How would you rate the quality of the financial institutions that serve this neighborhood, such as banks, savings and loans, or other places where you can hold your money?* A multilevel Empirical-Bayes technique was, again, used to combine responses and estimate a neighborhood-level resource-quality score. Neighborhoods with higher scores on this scale represent neighborhoods with elevated access to higher quality resources. Institutional resource-quality scores range from approximately 2.10 (poor neighborhood resources) to 3.42 (excellent neighborhood resources).

Additional individual-level measures are included as controls (**X**). These include a measure of one's interviewer-observed gender (1 if observed as female; 0 if observed as male); one's self-reported race/ethnicity (1 if Hispanic/Latinx; 2 if White; 3 if Black; 4 if other); one's age (in log-years); one's immigrant generation (1 if first generation; 2 if second generation; 3 if third, or higher, generation); and one's parental education (if one's highest educated parent has at least college degree; 0 if otherwise).

4.5 Methods

To describe how educational gradients vary across neighborhoods, I estimate three Bayesian multilevel logistic regression models. The first model (*Model 1*) regresses self-rated health (*Y*) on education level (*A*). In this initial model, both a random (i.e., group-specific) intercept and education parameter are also estimated for each neighborhood. The random-education parameter associated with each neighborhood-cluster gives a conservative estimate of how strongly associated education and health are among that specific cluster. (Because CCAHS only has a handful of respondents per neighborhood, I expect for discrete neighborhood-effects to be fairly well-shrunk towards the mean. Only individual neighborhoods with particularly strong/weak educational gradients will be able to deviate from the overall mean.) The spread of group-specific educational param-

eters provides a coarse summary of how variable educational gradients are across neighborhoods in the data. (A greater spread in effects indicates more variability in educational gradients across neighborhoods.)

For a more precise understanding of how the association among education and health varies across neighborhood conditions, *Model 2* and *Model 3* regress self-rated health (Y) on education (A), a neighborhood characteristic of interest (either Z_1 or Z_2), their interaction ($A * Z_1$; $A * Z_2$), and the controls described above (\mathbf{X}). To allow for these models to coherently pool strength across individuals situated in different neighborhood spaces, a random intercept is estimated for each discrete neighborhood-cluster as well. (To account for potential non-linear effects, I also examine models that include a second-order polynomial for each neighborhood-level feature (e.g., neighborhood hazards, squared). In approximate leave-one-out cross-validation tests (Vehtari et. al. 2017), that compare the predictive accuracy of models with and without the additional polynomial term, the simpler model is preferred in both cases.) Models 2 and 3 estimate the probability of reporting excellent/very good self-rated health, given one's education, personal attributes, and neighborhood context. Using these models, I compare estimates of self-rated health for individuals with and without college degrees across varying neighborhood conditions, while holding all other features constant at their means.

Bayesian models with weakly informative priors are chosen for this analysis as they help regularize estimates—e.g., prevent single, small-sample size neighborhoods from having over-sized influence on model results—and stabilize computation (Gelman et. al. 2008). Bayesian multilevel models also have the advantage of producing credible intervals (or confidence intervals) that accurately incorporate uncertainty produced at all levels of the model (Fox and Weisberg 2011). All point-estimates and credible intervals are obtained by sampling from model posterior predictive distributions. Models are fit using the `rstanarm` package (Stan Development Team 2016) in the R statistical programming language (R Core Team 2018). Priors are set to their default values in `rstanarm`, which have been shown to aid computation/regularization across a (very) wide-range of

scenarios. (The intercept prior is normal with mean 0 and standard deviation 10 (after centering); the coefficients on the predictors have normal priors as well, with mean 0 and standard deviation 2.5. All components of the prior covariance matrix associated with group-specific terms are set to 1. Please see the `rstanarm` documentation (Stan Development Team 2016) for more information).

4.6 Results

To aid interpretation of results, I begin by describing the CCAHS sample population. The CCAHS sample is comprised of a mixture of individuals. Among the $n = 3,105$ respondents, $n = 724$ have college degrees and $n = 2,381$ do not. 60% of the sample—approximately 1,870 respondents—are coded as *female*, while the rest are coded as *male*. Race is distributed fairly uniformly, with 26% of the sample identifying as *Hispanic/Latinx*, 32% as *White*; 39% as *Black*, and 3% as another race/ethnicity. The median age is 40 years old—with the 25th and 75th quantiles being 29 years and 53 years old, respectively—and the majority of individuals (approximately 63% of the sample) are classified as at least third-generation immigrants.

To characterize the neighborhood spaces that define the data, Figure 4.1 plots the distribution of respondents, by education level, across the 343 distinct neighborhood-clusters.

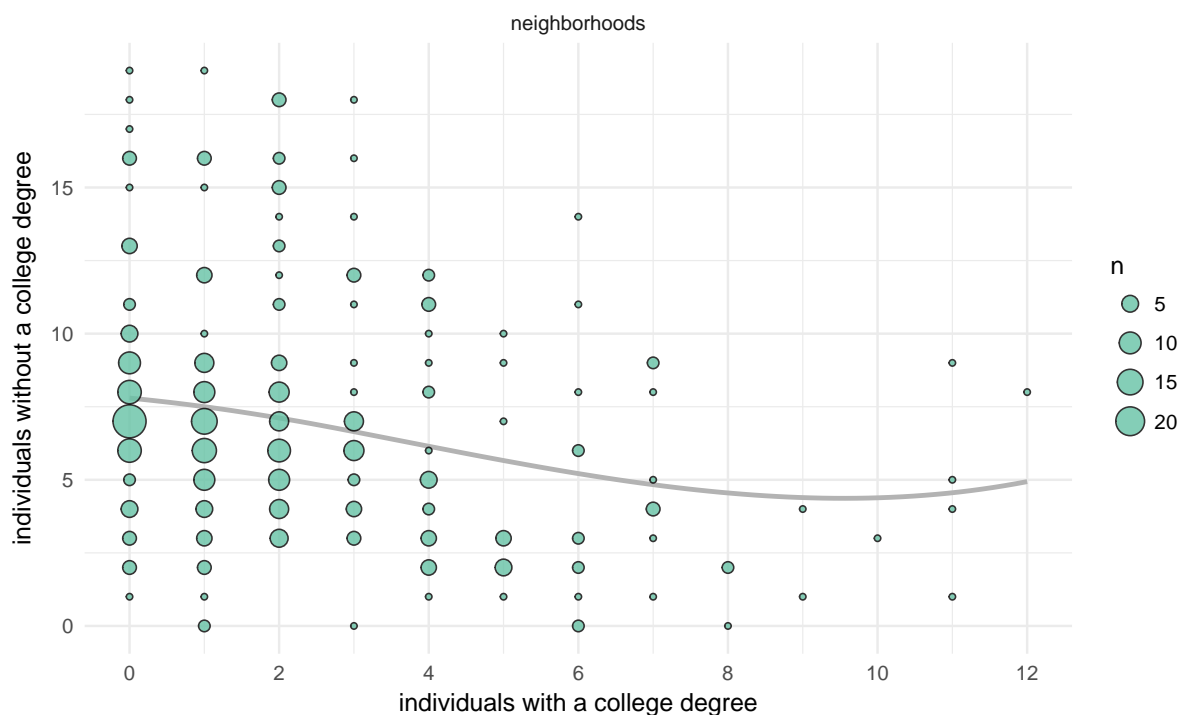


Figure 4.1: Count of neighborhoods with with x number of college educated individuals and y number of non-college educated individuals. The light-gray line represents a smoothed relationship among the two counts.

Figure 4.1 shows that the 724 individuals with college degrees and the 2,381 individuals without college degrees are spread fairly well across the 343 neighborhoods in the data. While an expected, slightly negative relationship exists among the two counts—in that as the number of college educated individuals increases in a neighborhood, the number of non-college educated individuals decreases—many neighborhood clusters contain a mixture of individuals at different levels of personal educational attainment. On average, each neighborhood contains 9 respondents, 2 of who hold a college degree and 7 of who do not. The smallest neighborhood cluster contained one respondent, while the largest contained 21.

To further characterize the neighborhood spaces that CCAHS respondents occupy, Figure 4.2 plots the observed relationship among neighborhood hazards, neighborhood institutional quality, and educational attainment.

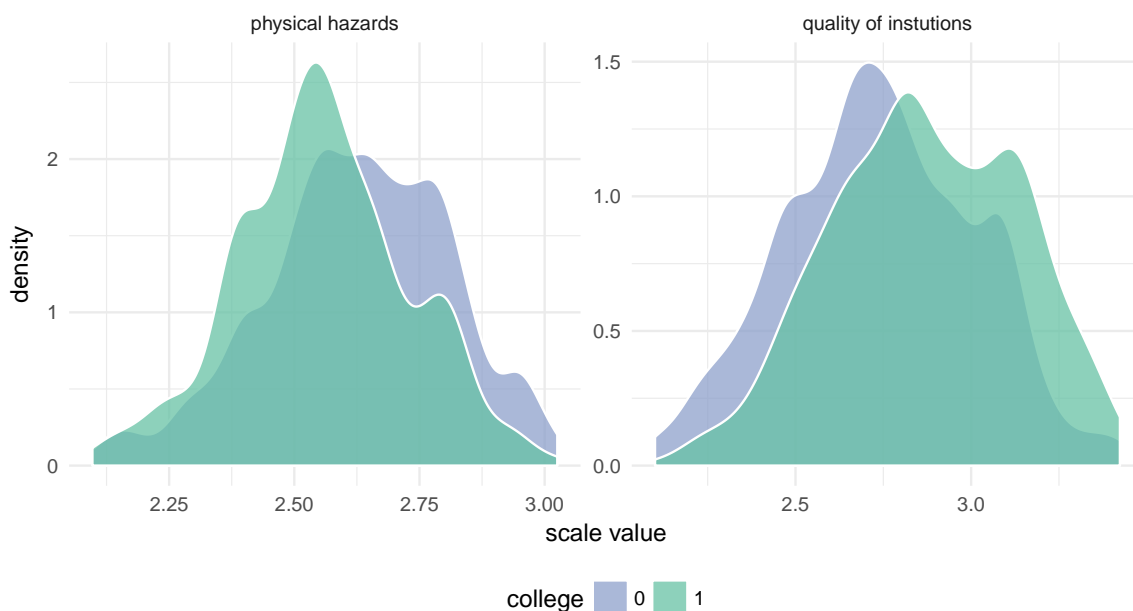


Figure 4.2: Distribution of neighborhood hazards and institutional quality scales among all individuals in the data. Green densities represent distributions among college educated individuals; blue-shaded densities give distributions among individuals without a college degree.

Figure 4.2 shows that both college and non-college educated individuals experience a range of neighborhood conditions. On average, college educated individuals reside in neighborhoods with with hazard scores of 2.54 and institutional quality scores of 2.90. Hazard scores are somewhat higher among non-college educated individuals (~ 2.65) while institutional resource scores are lower (~ 2.75). Note that, despite the improved neighborhood conditions among the college educated sample-population on average, education

is not *deterministic* of neighborhood risk/quality; individuals with and without college degrees are spread into various neighborhood contexts in these data.

Educational attainment and neighborhood characteristics appear to share strong, independent associations with health in the data. Among non-college degree holders, 44% are in excellent/very good health; among college degree holders, 72% report superlative health. (College educated individuals are thus observed to be 1.65 times more likely to report excellent/very good health.) Both neighborhood characteristics show similarly strong associations with self-rated health: the observed probability of excellent/very good health shrinks from approximately 60% among individuals in the least hazardous neighborhoods to 37% in the most hazardous neighborhoods, while the observed probability of excellent/very good health grows from nearly 34% in the lowest quality-resource neighborhoods to 75% in the highest quality-resource neighborhoods.

To assess how neighborhood environments and education *interact* to affect health, we turn to the models described above. Figure 4.3 plots the estimated association among education and self-rated health across neighborhood clusters, as represented by the random-education parameter from Model 1.

Figure 4.3 shows that the association among education and health fluctuates across neighborhood spaces. In the average neighborhood, the *odds* of being in excellent/very good health are 3.30 times higher for individuals with a college degree compared to individuals without a college degree. Given the relatively small sample sizes contained within any given neighborhood space (9 individuals per neighborhood, on average), many neighborhood specific effects shrink towards this mean value. Despite this intended preference for shrinkage/to be conservative, a number of neighborhoods display estimated educational gradients that spread away from the average. Indeed, among neighborhoods where education is least impactful for health, college educated individuals are estimated to experience odds of self-rated health that are only 2.5 times more than odds among non-college educated individuals. In spaces where educational attainment is most conse-

quential, estimated odds-ratios approach 4 to 1.

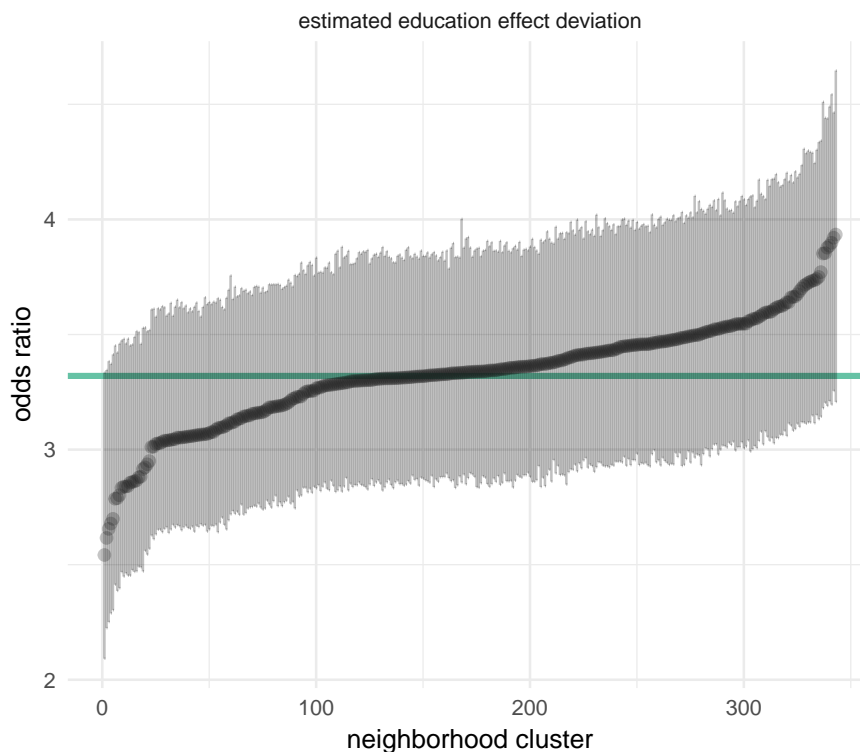


Figure 4.3: Estimated association (in odds-ratio; college degree/no-college degree) among education and self-rated health across CCAHS neighborhoods. Note that the solid-green line marks the average odds-ratio estimate. Grey bars represent 50% posterior intervals.

For a more precise understanding of how neighborhoods alter educational gradients, estimates that pool power across neighborhood clusters and estimate the impact of specific neighborhood characteristics are needed. Figure 4.4 displays how the probability of reporting superlative self-rated health changes across individuals with differing levels of education, in neighborhoods with varying levels of physical hazards (as estimated from Model 2).

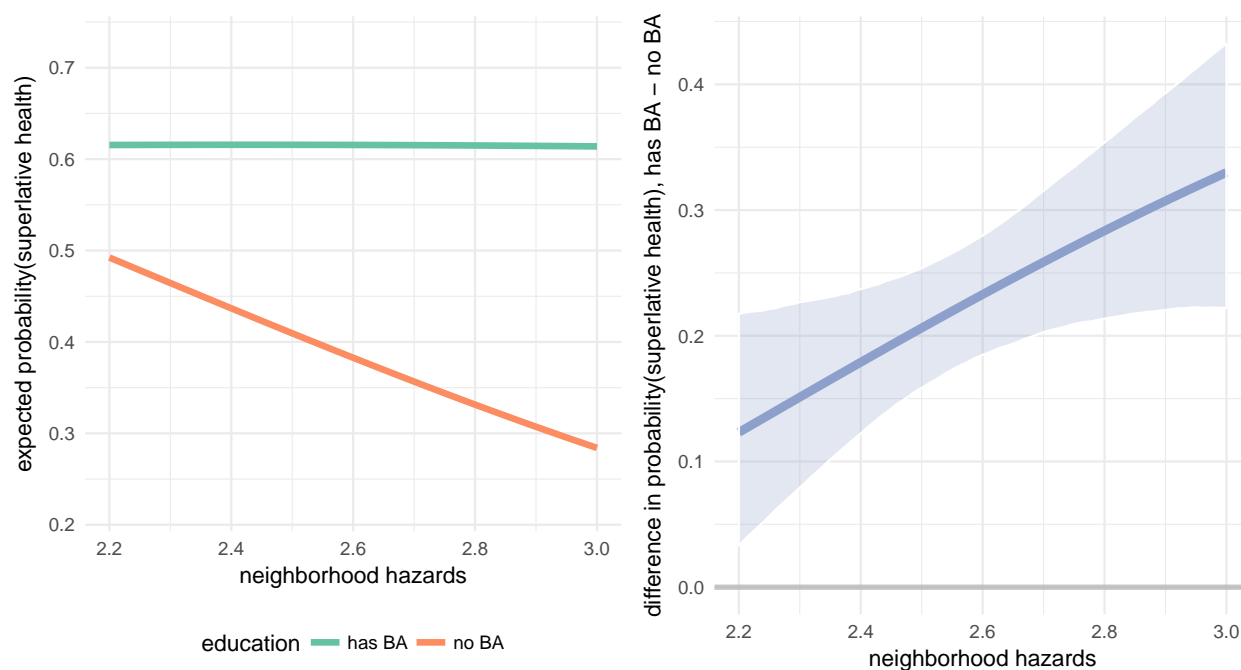


Figure 4.4: Predicted probability of excellent/very good health across varying levels of education and neighborhood hazards. 95% credible intervals are marked for the difference in predicted probabilities of self-rated health across education levels.

Figure 4.4 shows that a pronounced, interactive association exists among educational attainment, neighborhood hazards, and self-rated health. In neighborhoods where exposure to physical hazards are low, the predicted difference in the probability of reporting excellent/very-good health between college and non-college educated individuals is also low. (Among the least hazardous neighborhood environments, the difference in the expected probability of superlative self-rated health between the two educational groups is only 11-percentage points). The educational gradient in health grows with neighborhood hazards, such that college educated individuals are nearly 35 percentage-points more likely to report superlative self-rated in the most hazardous of neighborhoods environments. Note that the growth in educational disparities that accompanies increasing

neighborhood hazards is entirely a product of changes among non-college educated individuals. Individuals with a college degree are estimated to achieve the same level of self-rated health *regardless* of their level of exposure to neighborhood hazards; the health of non-college educated individual drops precipitously with increased exposure to detrimental neighborhood conditions.

Similar to Figure 4.4, Figure 4.5 gives the predicted probability of excellent/very good health as a function of education and neighborhood institutional quality (as estimated in Model 3).

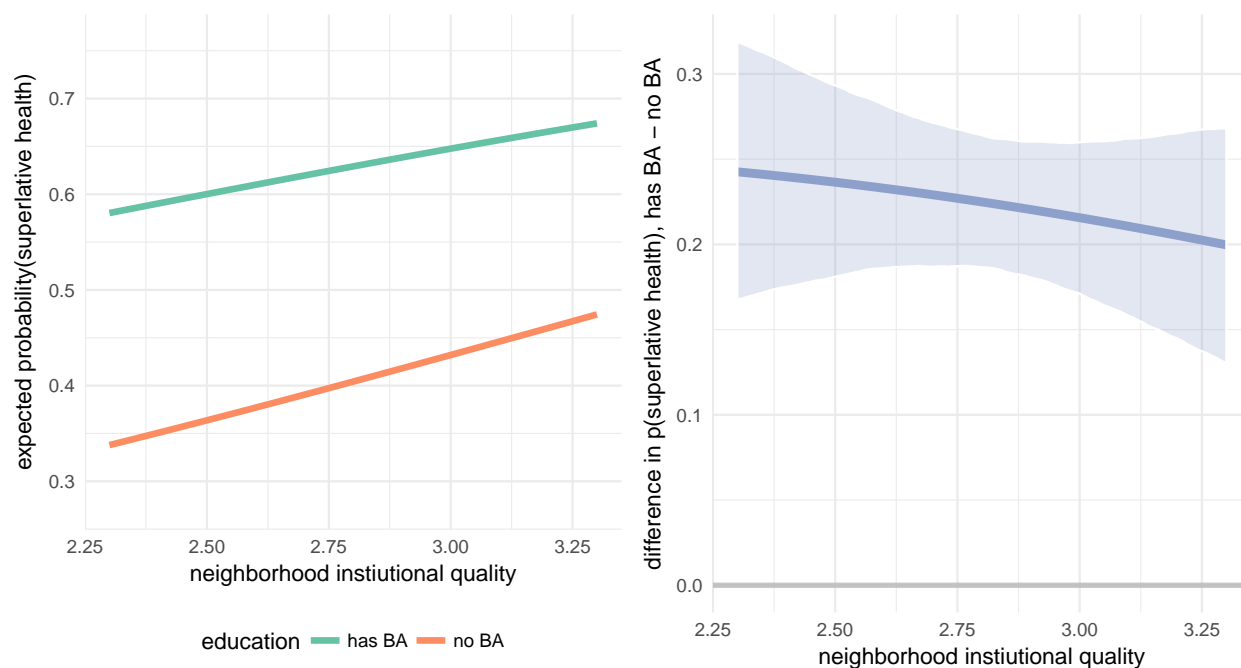


Figure 4.5: Predicted probability of excellent/very good health across varying levels of education and neighborhood institutional quality. 95% credible intervals are marked for the difference in predicted probabilities of self-rated health across education levels.

Figure 4.5 shows that, unlike with neighborhood hazards, the health of both college

and non-college educated individuals is impacted by neighborhood institutional quality. Among both educational groups, individuals in neighborhoods with better quality organizations experience greater self-rated health than individuals in spaces with poor collective resources. That both college and non-college educated individuals benefit from living in spaces with more abundant, high quality resources implies that this neighborhood feature has little to no impact on educational disparities in generalized well-being. Indeed, college educated individuals are predicted to be between 20 to 24-percentage points more likely to be in superlative self-rated health across all levels of neighborhood institutional quality.

4.7 Discussion

Using multilevel data from the CCAHS and Bayesian multilevel logistic regression models, this study provides estimates of how neighborhood contextual environments interact with personal educational attainment to affect well-being. Like other authors who have investigated how “context matters” for educational gradients in health (e.g., Cambois et al. 2016; Montez et al. 2017), I find that neighborhood environments alter how tightly coupled holding a college degree is with well-being.

As initially predicted, I find that educational gradients in health are particularly sensitive to neighborhood hazards. In neighborhoods defined by low-levels of physical hazards, health differences between college and non-college educated individuals are at their least. In environments where exposure to damaging conditions are high, educational gradients swell, by a factor of nearly three, because the health of non-college educated individuals degrades substantially. This result aligns with Montez et al.’s (2017) assertion that education acts as a buffer against suboptimal contextual conditions; indeed, I find that individuals with college degrees appear able to leverage their credentials to protect against health-damaging exposures that their neighborhoods place upon them.

Results for institutional quality run counter to initial expectations. Individuals in neighborhoods with more abundant, high-quality resources fare better than individuals

in less resource-rich environments, regardless of their level of educational attainment. Indeed, results show that both college and non-college educated individuals benefited, at approximately the same rate, from living in spaces with more quality resources. Educational disparities remained constant across neighborhoods with varying resources as such.

Paired together, these results highlight education, empirically, as a fundamental cause of disease (Phelan et. al. 2010) and frame a potentially important narrative for how education factors into health inequality. The health of low-education individuals appears to be sensitive to their immediate surrounding-contexts, on the whole. High-education individuals, on the other hand, appear able to engage with neighborhood spaces when doing so is good for their health and build barriers when engaging with the outside world when doing otherwise would be health-degrading. These results suggest that education's effect on health may, in no small part, be constituted by the control that it offers over one's immediate environment. Indeed, results suggest that *education allows individuals to engage flexibly and optimally with their immediate contextual environments in ways that preserve and promote health*. Empirical studies that formally test how neighborhood environments act as *mechanisms* of education's health effect may prove insightful for fleshing this idea out further. Likewise, studies that examine how other neighborhood-organized features—such as a neighborhoods' socio-cultural climate or political clout—affect education-induced health benefits would add additional nuance to this narrative.

This study is certainly not without limitations. CCAHS, while rich along many dimensions, is limited in *pretreatment (i.e., pre-educational attainment) confounders*. How respondents came their current level of educational attainment and their current health is likely intertwined and largely unobserved in these data. Without better control over these confounding features, results should *only* be interpreted as associations and not as causal relationships. (Similar issues with confounding define many social science research questions (Hill 2011).) Future research should utilize in-progress data collection efforts, that better record confounding processes across the life-course (e.g., *High School*

and Beyond: Midlife Follow Up (Warren et. al. 2017), to assess results under stricter causal assumptions. Moreover, although self-rated health is informative, in that it is a distinct dimension of well-being and powerful associate of many other health outcomes (Jylha et. al. 2006; Jylha 2009), it is a relative coarse assessment of one's health. The joint influence of education and neighborhoods should be examined on other health outcomes for additional perspective. (Note that preliminary results of body mass index and sleep problems point to the same patterns observed here.) Additional measures of neighborhood hazardous and institutional quality should similarly be examined to further bolster results. Additional research that examines how these patterns generalize to other cities should also be pursued.

Altogether, this study adds to a burgeoning ensemble of voices across the population-sciences that position health as *inherently multilevel* (e.g., Diez Roux 2008; Hayward et. al. 2015; Hicken et. al. 2018; Montez and Friedman 2015; Montez et. al. 2017). Individuals are, inescapably, embedded within health-relevant social, cultural, and physical spaces, and contextual-environments lack health-relevance absent the individuals who reside in them. That the personal and contextual are necessarily adjacent to one another suggests that their effects on health may, as this study shows, be as well. Both empirical and theoretical efforts that explicate how personal-level and contextual-level forces coalesce to generate health may be key for best understanding how health manifest among any given population. The conjoint effects of individual-level and higher-order features may be particularly essential for understanding health among groups of individuals who face marginalization on multiple levels of social-organization and should thus be investigated, in force, to potentially address population health disparities.

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Chapter 5

CONCLUSIONS: SOCIAL CONDITIONS AS SIMULTANEOUS DETERMINANTS OF HEALTH

Social factors are, at this moment, inarguable determinants of population health (Hayward et. al. 2015; Phelan et. al. 2010). Social attributes—such as racial assignment or level of educational attainment—inform all aspects of well-being. How individuals experience a mixture of salubrious material and social resources, as well a number of health-degrading experiences and exposures, is indeed shaped by the social position that they occupy. Empirical work that underpins this insight, of social conditions as fundamental causes of health, is robust in that in it is well-pursued; innumerable studies, produced by researchers from across substantive and methodological traditions, have cataloged how any-given-health-outcome is impacted by any-given social-feature (Harper and Strumpf 2012; Kawachii et. al, 2010).

Despite its strengths, knowledge of how social conditions act as determinants of health is still developing. Individuals *necessarily* embody multiple social-conditions, simultaneously. (Any given member of a racial population certainly has a level of educational attainment and any individual with a particular level of educational attainment is invariably assigned a racial category, for instance.) That social conditions *always* exist adjacent to one another, within individuals, suggests that their effects on health may be adjacent too (Bowleg 2012). Empirical literature has only recently begin to investigate this potentially important complexity; research that clarifies how the multiple positions that individuals occupy coalesce and affect health is at a premium as such (e.g., Bauldry 2015; Montez and Friedman 2016; Brown and Hargrove 2013; Sasson 2016).

The aim of my dissertation project was to help build empirical foundations around

this idea, of the joint influence of multiple social conditions on health. In three studies, I examined how race—and social features organized by race—comes to bear in educational gradients in health. By going beyond *just* documenting differences in population averages and effect-sizes, these studies demonstrate the multiple and complex ways that the association among education and self-rated health varies among Blacks and Whites in the US. Below is a discussion of the insights yielded by each analysis.

5.1 Recap and contributions

Chapter 2—*Inequality in Process*—sought to clarify why Black-White differences exist in the health returns to a college degree. Using sequential g-estimation and data from The National Longitudinal Study of Adolescent to Adult Health, I found that income diverged across Black and White sample-populations in how it participated as a mechanism of education's effect on health. Among Whites, income behaved as one might expect; income played a significant role in generating the improvements to well-being experienced by college-educated individuals and only intensified in this capacity as income increased. Among Blacks, however, income played little to no role in explaining why attaining a college degree was beneficial for one's health. That educational effects were strongly dependent on income among Whites but not among Blacks—and that income is a prime mechanism through which education is hypothesized to affect health—suggests that income plays a central role in generating Black-White heterogeneity in educational gradients.

Perhaps more importantly, Chapter 2 demonstrated that the interaction among race and education runs deep, in that race fundamentally alters how education is leveraged as a health-protective resource. Though average educational effects among Blacks were only 5 percentage points less than average effects among Whites, the mechanical processes that undergirded these outcomes diverged quite noticeably across sample-populations. (Indeed, racial groups differed more in terms of *how* a college degree benefited health than in *how much* a college degree benefited health.) Altogether, Chapter 2 highlights

that only documenting average-magnitude differences in outcomes can conceal complexity in how socially-distinct individuals experience the same social-processes. Chapter 2 suggests that, to best understand how multiple social conditions interact to effect health, efforts must go beyond cleaving individuals into groups defined by said conditions, and calculating and comparing within-group average-effects. Instead, efforts that parse how the underlying process that ties a given social condition to health is itself impacted by other social conditions should be pursued when investigating such interactions.

The next empirical chapter—Chapter 3, *Inequality in Effect*—added depth to this project by more fully describing how education and health manifest within Black and White *populations* in the US. Most work that has quantified racial differences in educational gradients has implicitly treated racial groups as monolithic, all-encompassing, categories. Often in these studies, a single, average educational effect is calculated for each racial group under examination and these group-specific means are compared as a summary of how effects vary across individuals situated in different groups. While this type of analysis is useful—in that average effects are those that typify a group—it also serves to collapse heterogeneous populations into single experiences. Understanding of how education acts as a determinant of health *within* specific racial-populations—and thus how education varies *across* racial-populations—is indeed largely constrained to how education operates among “average” individuals.

Chapter 3 found that moving descriptions of racial differences in educational gradients from *differences in average individuals* to *differences in populations* yielded additional information about how Blacks and Whites experience education as a social determinant of health. (Using data from Add Health and Bayesian Additive Regression Trees for response surface modeling, I found that experiencing measurable health benefits from educational attainment was somewhat more dependent on other social-attributes among Blacks than among Whites; and that educational attainment appeared to benefit marginalized individuals more among Whites and more privileged individuals more among Blacks.) Overall, Chapter 3 highlighted *the importance of focusing on populations in studies of population-*

health processes. Results from this analysis suggest that using multidimensional summaries to describe how social conditions operate on health within social-groups offers a more complete picture of how social conditions interact to produce health.

Chapter 4—*Inequality in Context*—took a different approach than the previous chapters. Instead of examining race directly, this chapter examined how a social-feature that is organized by race—i.e., neighborhood context—organizes educational gradients in health. Using data from the Chicago Community Adult Health Study and Bayesian multi-level logistic regression models, this chapter demonstrated that how tightly coupled education is with health is highly conditional on one's immediate, surrounding environment. Perhaps the most striking result from this chapter showed that attaining a college degree was essential to maintaining positive self-rated health in spaces where exposure to external hazards were high and minimized in protecting health among neighborhood spaces where exposure to physical hazards were low. Results from this chapter also showed that both college and non-college educated individuals were equally able to draw upon the positive dimensions of their surrounding environments to protect health. Altogether, Chapter 4 shows that education functions to protect health by offering individuals a level of control over how/when they interact with their environments.

This interaction—among personal educational attainment, neighborhood environments, and well-being—may be particularly important for understanding health among Non-Hispanic Black individuals. Indeed, due to systematic, racial residential segregation, the association among education and salubrious residential traits is decoupled among Blacks, relative to Whites (Williams et. al. 2016). (The probability of experiencing poor neighborhood conditions is higher among college-educated Blacks than college-educated Whites, for instance.) Education may be an especially important resource for Blacks to protect against poor health in a social structure that systematically bars them from otherwise health-protective contextual resources. Data with larger sample sizes of individuals of different races and individuals in distinct neighborhood spaces than are available in

CCAHS are needed to test this idea formally; results from Chapter 4 suggests that pursuing this research question would be productive.

5.2 *Limitations and future research*

As informative as the studies in this dissertation are, they function primarily as the foundation for an ongoing research agenda. Indeed, race was shown to enter into the relationship among a college degree and self-rated health along several, elaborate, dimensions. Yet, these studies only scratch the surface of the multiple ways that race might come to bear in educational gradients in health. Clarifying how education and race interact to produce variable health outcomes among the US population is an extensive project that will require ongoing input from additional researchers. The limitations of the studies presented here offer some perspective on how to move this agenda forward.

In terms of general limitations, altering the operationalization of both race and education offers the most straightforward path for expansion of these projects. In each chapter, race was constrained to only *non-Hispanic Black* or *non-Hispanic White* individuals, and education was always defined around an individual's college completion status. While limiting analyses to these few categorical distinctions allowed for more precise inference, doing so also discarded salient information about how individual's of other racial/ethnic groups experience other levels of educational attainment as a health-protective force. More dynamic approaches to defining race (e.g., incorporating Asian and Latinx populations; defining *racial assignment* with compound measures, that allow for multi-racial or ethnicity-specific distinctions) or to defining educational attainment—e.g., investigating high-school or 2-year colleges as treatment levels; splitting the sample along non-traditional forms of schooling that are increasing in prevalence, such as online-only or for-profit colleges—are needed to add further nuance to this project. A rich catalog of empirical studies that document how all iterations of racial-categorization act in conjunction with all forms of educational attainment would add tremendous precision to

this dissertation's end goal.

Another shared limitation of these projects is their *exclusive* reliance on self-rated health as response/outcome. Self-rated health is a valuable marker of well-being for these studies, in that it is associated with a wide-range of health measures that co-vary with educational attainment (e.g., mortality; recurring health problems; physical tiredness; stress; underlying biomarkers) (Jylha et. al. 2006; Jylha 2009) and in that it has been shown to share a causal relationship with college completion (particularly among the populations represented in Add Health) (e.g., Lynch and von Hippel 2016). The results of these projects, though, should not be assumed to generalize to all health outcomes (even those associated with self-rated health). Distinct health outcomes are constituted by distinct underlying processes; separate studies, that examine how race enters into the process that ties educational attainment to any other given health outcome, are needed as such. Documenting for which health outcomes the above patterns hold—and for which they do not—can add additional resolution to the above projects and should thus be pursued further.

Clarifying how any two social conditions, beyond just race and education, function as simultaneous determinants of health is an even more immense research agenda. Shifting population health studies towards more fully incorporating the idea that social conditions act as simultaneous, necessarily-interwoven determinants of health will require the collective efforts of health-scientists situated across substantive and methodological traditions. The research presented here provides some general framing for moving this agenda forward. In particular, this project suggests that efforts to clarify how multiple social conditions influence health should directly examine underlying processes, rather than just magnitudes; focus on populations and multidimensional summaries, rather than just group-averages; and examine how social conditions interact in conjunction in-

directly (i.e., through third variables) to produce health.

5.3 Concluding remarks

Overall, this dissertation demonstrates a rich and fundamental interaction among education and race in their influence on health. How education matters for health varies, in multiple and complex ways, across populations of individuals defined by a shared racial assignment. More generally, this dissertation provides evidence that social condition-health processes inherit the complexities of the individuals they operate on. No social condition exist within a vacuum, but rather always adjacent to other social determinants of health. Folding this inherit complexity into empirical investigations of health and health disparities adds needed nuance to our understanding of how social conditions participate in population health.

5.4 References

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Appendix A

CHAPTER 3 CONFOUNDERS

Table A.1 provides short definitions for all variables used in the analysis. Note that the self-esteem measure is comprised of the following items: *Do you agree or disagree with the following statement: (1) you feel like you are doing everything just about right; (2) you feel loved and wanted.; (3) you feel socially accepted; (4) you have many good qualities; and (5) you have much to be proud of.*

Table A.1: Description of pretreatment confounders included in the analysis

measure	definition	values
sex category	reported sex category	1: male; 0 female
age	age at W4	in years
skin tone	interviewer assessed skin tone	1: dark; 2: medium; 3: light
nativity status	born in the US or elsewhere?	1: born in US; 0 otherwise
w1 home language	primary language spoken at home	1: English; 0: other
w1 attractiveness	interviewer rated attractiveness	1: (very) attractive; 0: if other
w1 depression	CES-D 9 item score	higher = more depressive
w1 self-rated health	self-rated health at W1	1: excel./v. good; 0: good; -1: fair/poor
w1 sick days	missed school days due to health	0: never; to 4: everyday
w1 hours sleep	average hours sleep a day	hours (<= 3 to => 12)
w1 suspended	ever suspended from school	1: yes; 0: no
parent education	education of highest educated parent	0: no HS; to 3: BA or more
parents in household	lives with two parental figures	1: yes; 0: no
parent nativity	has US born parent	1: yes; 0 no
w1 parent aid	parent receiving social support	1: yes; 0 no
w1 impulsiveness	go with gut, w/o think of consequences	1: strong agree; 5: strong disagree
w1 self-esteem	sum of 5-items related to self-perception ¹	higher = greater self-esteem
w1 upset by problems	agree that difficult problems upset you	1: strong agree; 5: strong disagree
w1 drinking behavior	count of times had a drink past year	0: never; to 6: every day
w1 violent delinquency	count of times serious fights past year	0: never; to 5: 5+
w1 nonviolent delinquency	count of times damaged property past year	0: never; to 5: 5+
w1 arrested	if been arrested before 18th birthday	1: yes; 0 no;
w1 college expectations	how much believes will attend college	-2: low; +2 high
w1 social support, parents	how much believes parent cares about	1: not at all; 5: very much
w1 social support, teachers	how much believes teachers cares about	1: not at all; 5: very much
w1 perceived discrimination	how much believe peers are prejudiced	1: strong agree; 5: strong disagree
w1 pvt score	score on Peabody Picture-Vocabulary Test	higher = better performance
w1 math grade	grade in most recent math class	4: A; to 1: D/F
w1 english grade	grade in most recent English class	4: A; to 1: D/F
w1 ACEs, physical	count of times experienced physical abuse	0: never; 5: 10+
w1 ACEs, sexual	count of times experienced sexual abuse	0: never; 5: 10+
w1 region	if residing in South	1: yes; 0: no
w1 urban-rural	urban-rural classification of area	1: urban; 2: suburban; 3: rural
w1 block-group income	average income of block-group	(log) dollars
w1 block-education	percent of block-group with a college degree	percent
w1 school Master's	percent of teachers at school with Master's	percent
w1 average class size	average class size at school	number of students
w1 public school	attends private or public school	1: public; 2: private

Appendix B

CHAPTER 4 MODEL PARAMETER ESTIMATES

Figure B.1 displays the parameter estimates from the regression models used to generate predictions in Chapter 4—i.e., the parameter estimates for Model 2 and Model 3.

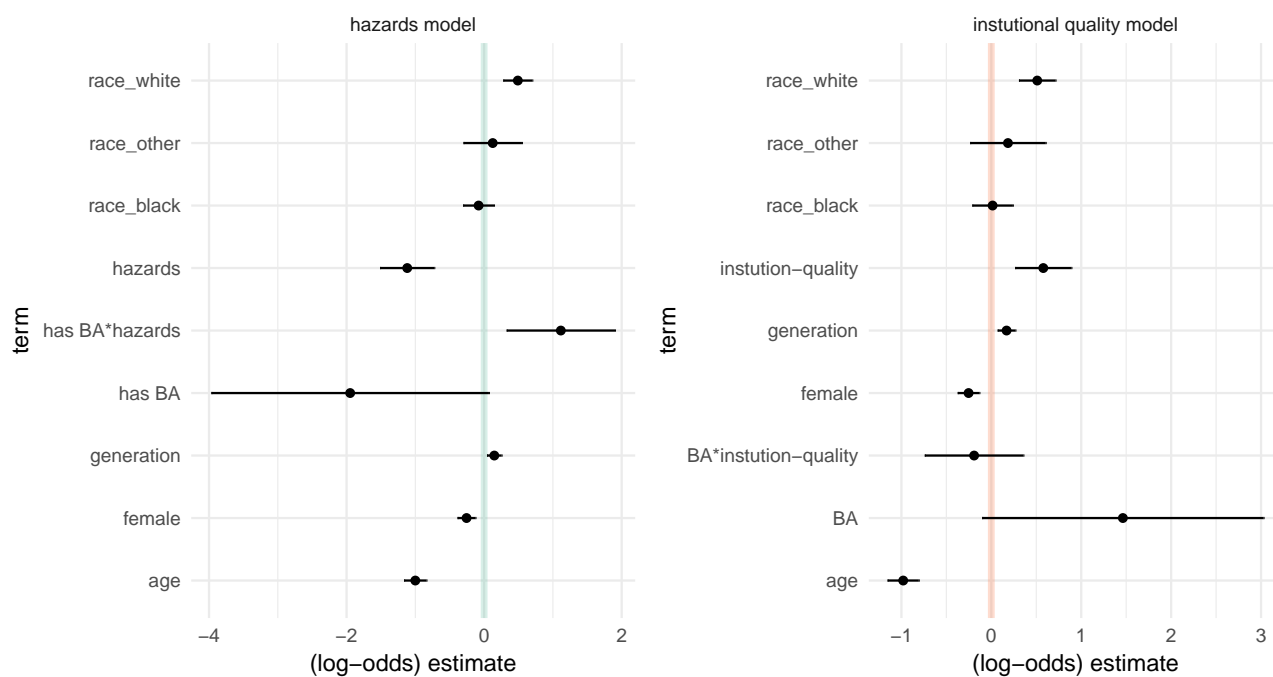


Figure B.1: Fixed parameter estimates from logistic regression models from Chapter 4. Estimates are given in log-odds and 95% uncertainty estimates are marked.

VITA

Michael Esposito is a sociologist whose works focuses on clarifying how *race matters* in population health. (This includes: (1) explicating how and why racial disparities in health outcomes are generated, rather than just quantifying the size of said inequalities; (2) connecting broad, structural features that are related to race (e.g., mass incarceration; residential segregation) to health outcomes/disparities; and (3) examining how other social-locational attributes that organize US society intersect with race to stratify health). In Fall 2018, Michael will begin a postdoctoral position at the University of Michigan's Survey Research Center.