CLOSING THE RACIAL GAP IN HYPERTENSION

THE ROLE OF WORK INEQUITY AND OCCUPATIONAL SEGREGATION

A DISSERTATION SUBMITTED TO THE FACULTY OF
THE UNIVERSITY OF MINNESOTA BY

Tongtan Chantarat

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR
THE DEGREE OF DOCTORAL OF PHILOSOPHY

CO-ADVISORS

Eva A. Enns, PhD, MS
Rachel R. Hardeman, PhD, MPH

SEPTEMBER 2021

ACKNOWLEDGEMENT

First and foremost, I want to thank **my parents**, especially **my mom**, who lost her fight to pancreatic cancer last year. I would not have pursued a PhD at all without encouragement from her. Mom, I am proud to be your son, and I hope to be a good educator for the next generation of public health scholars like you did for thousands of your students.

To my husband, **John Kelly**, thank you. Period. You are the first one I called when I got into this program. I remember telling you that "Oh my god, I now have a future…but I have to move to Minneapolis." Long-distance relationships are very hard, let alone long-distance marriages. I think these past five years made us stronger as a couple and taught us what it means to "make it work." I know the past few months has been rough for us as I was wrapping up my dissertation. I am looking forward to the post-PhD life with you. I promise not to overwork or prioritize chasing a tenure above spending our life together. [I may ignore you from time to time when I have paper or proposal deadlines.]

Dr. Martin Luther King once said, "If you can't fly, then run. If you can't run, then walk. If you can't walk, then crawl. But whatever you do, you have to keep moving forward." I truly believe that to finish a dissertation, ones must do just that. Although I was not able to fly and was just trying to run really quickly so I can jump, I was doing this under the watchful eyes of a group of mentors who really want to see me succeed and…fly.

To **Dr. Eva Enns**, thank you for letting me run free with my ideas. You are the first person I met in Minneapolis on the campus visit day in March 2016. Who would have thought that the person who told you then that he wanted to study diabetic retinopathy screening ended up a racism scholar? Your openness to the nontraditional application of decision science methods, especially in areas you have limited content knowledge about, is inspiring. Thank you for being very flexible with me (e.g., Zoom project meetings, sometimes with a 12-hour time difference, when most people didn't even know what Zoom means) and being supportive of all my endeavors. I aspire to be a mentor like you.

To **Dr. Rachel Hardeman**, thank you. I would not have been the racism scholar I am today without your guidance. You are my superior for the past five years, but I have never once been made to feel like I was just your RA. Thank you for being my mentor and, many times, emotional support. You taught me how to navigate the academic world (the racist one, that is) and showed me how to be successful in every stage. I look forward to our future collaboration as colleagues and working toward dismantling structural racism together.

To **Drs. Pat McGovern, Sam Myers, Janette Dill, and Donna McAlpine**, thank you for your mentorship and for providing your expert insights on my project. People often ask if I am an epidemiologist, occupational science scholar, economist, sociologist, or decision scientist. I can only say that I am a bridge between these fields, able to translate cryptic language from one field to communicate to those in other fields and leverage multidisciplinary strengths to advance my scholarship because of your mentorship. I also want to thank **Drs. Karen Kuntz** and **Ira Moscovice** for their academic and emotional support.

To my friend **Dr. Anne Eaton**, thank you for the most incredible emotional support throughout the five years. My life in Minneapolis would have been unbearable without a New Yorker friend like you. You are my biostat extraordinaire. You lent me your sofa when I flew into town to check in with my advisors. You are the only person in Minneapolis who has met John. You are the one person with whom I look forward to having a Friday drink at DCBC. While I will not be crashing on your sofa after I finish my PhD, I look forward to visiting you in your new home and hang out with you when I visit Minneapolis in the future.

To my friend **Sarah Sala and Christina Quintana**, thank you for your friendship and for being there for John and I when we need. We will never have survived a New York-Bangkok lockdown during the pandemic without having you two "close by." I am glad our dog children are growing up together.

To my child dog **Archie Kelly-Chantarat**, you are a pain from time to time. But you also bring joy to my and your daddy's lives. You nip me to let me know it is 5 pm and to stop working and to take you out to poop and play with your dog friends. You wake me up in the middle of the night because you want to poop. But, despite all those, your daddy and I love you and cannot wait to bring you along with us to start the next chapter of our lives.

Support for this research was provided, in part, by the: National Institute for Occupational Safety and Health (NIOSH), Centers for Disease Control and Prevention, Department of Health and Human Services and the Midwest Center for Occupational Health and Safety (NIOSH Training Grant Number T42OH008434).

DEDICATION

ให้แม่

I hope I made you proud.

ABSTRACT

Health inequities between Black and White workers are persistent problems in the United States. To address these problems, scholars and policymakers have put their effort into minimizing workers' exposure to occupational health risks and providing high-quality healthcare when workers get sick. However, while these initiatives help improve workers' health overall, limited progress toward racial health equities has resulted from these initiatives.

Grounded on the social production of workers' health inequities framework, this dissertation critically examined the role of work as a social determinant of health and the extent to which work inequity and occupational segregation create and sustain workers' health inequities. Black workers are more likely to work in occupations with high occupational health risk exposure and a high likelihood of unemployment compared to White workers. Hence, Black workers are systematically more vulnerable to getting sick yet can lose access to health-promoting resources like healthcare coverage more easily than their White peers. We argue that policymakers should prioritize eliminating work inequity and occupational segregation – what we referred to in this dissertation as "desegregation policies" - rather than those that correct the "symptoms" of racial health inequities.

Using hypertension inequity between Black and White healthcare workforces as a case study, we predicted changes in racial gaps in hypertension under various desegregation scenarios. This dissertation has four chapters. Chapter one introduces the social production of workers' health inequities framework. Chapter two describes our

efforts to derive a hypertension risk equation incorporating work-related factors, a key ingredient for a microsimulation to predict hypertension trends. Chapter three describes our microsimulation model and results from a counterfactual analysis. We predicted changes in the racial gap in hypertension under four desegregation scenarios relative to in the current occupationally segregated workforces. Lastly, chapter four discusses our early effort to validate our model prediction with real-world data.

Overall, this dissertation provides a novel framework and a methodology that scholars and policymakers may leverage for future efforts to eliminate workers' health inequities targeting upstream factors.

TABLE OF CONTENT

Acknowledgement	i
Dedication	v
Abstract	vi
Table of Contents	viii
List of Tables	x
List of Figures	xi
List of Appendixes	xiii
List of Abbreviations	xiv
CHAPTER 1: Dissertation Introduction	p. 1
CHAPTER 2: Predicting the Onset of Hypertension for Workers: Does Including Work Characteristics Improve Risk Predictive Accuracy?	p.8
2.1 Abstract	p.9
2.2 Introduction	p.10
2.3 Methods	p.13
2.4 Results	p.19
2.5 Discussion	p.27
2.6 Supplemental Materials	p.32

CHAPTER 3: Occupational Class, Power, and Hypertension Inequity: The Implication of the Inverse Hazard Law Among Healthcare Workers p.36
3.1 Abstract p.37
3.2 Introduction p.38
3.3 Methods p.46
3.4 Results p.54
3.5 Discussion p.60
3.6 Supplemental Materials p.65

CHAPTER 4: From A Cohort to A Population Model p.85
4.1 Motivation p.86
4.2 Methods p.89
4.3 Results p.93
4.4 Reflections and Next Steps p.97

BIBLIOGRAPHY p.100

APPENDIX p.115

LIST OF TABLES

TABLE 2.1: Analytical Sample Characteristics at Year 15 and Their Hypertension Status at Year 20 (n=1,909) p.20

TABLE 2.2: Logistic Regression Models Predicting Five-year Hypertension Onset and Their Validation Statistics p.23

TABLE 2.3: Comparison of the Mean C-statistics of the 200 Regression Models Estimated Using the Datasets That Consisted of All Black Participants (n=733) and the Same Number of Randomly Sampled White Participants (n=733) p.25

TABLE S2.1: Occupations of CARDIA Participants in Which the PWE Measures Could Not Be Assigned, Indexed by the 1990 US Census Bureau Occupational Codes p.35

TABLE 3.1: Model Parameters p.49

TABLE S3.1: Healthcare Occupational Classes and Their Proportional Representation in the White and Black Healthcare Workforces Based on the 2017 American Community Survey p.67

TABLE S3.2: Predicted Probabilities of Being in Each Occupational Class for 25-year-old Healthcare Workers Under the Status-quo and Four Counterfactual Scenarios p.80

TABLE S3.3: Descriptive Statistics of Job Demand, Job Control, and Support Measures by Occupational Class. p.82

TABLE S3.4: Mean Prevalence (Cases per 100) of Hypertension Among Black and White Healthcare Workforces by Age Group Under the Status Quo and Four Counterfactual Scenarios p.83

TABLE 4.1: Calibration Model Parameters and Outputs p.94

LIST OF FIGURES

FIGURE 1.1: Social Production of Workers' Health Inequities p.4

FIGURE 2.1: Sample Exclusion p.16

FIGURE 3.1: Proportional Representation of Four Occupational Classes in the White and Black Healthcare Workforces p.44

FIGURE 3.2 Hypertension State Transition Diagram p.48

FIGURE 3.3: Status-quo Simulation Output p.56

FIGURE 3.4: Comparison of the Black-White Prevalence of Hypertension Under the Counterfactual Conditions, Scenario A & B p.58

FIGURE 3.5: Comparison of Black-White Prevalence of Hypertension Under the Counterfactual Conditions, Scenario C & D p.60

FIGURE S3.1: Prevalence of Hypertension Among Healthcare Workers by Occupational Class and Race p.71

FIGURE S3.2: State Transition Diagram for Smoking Status p.75

FIGURE S3.3: State Transition Diagram for Physical Activity p.76

FIGURE S3.4: State Transition Diagram for Hypertension - *same as FIGURE 3.2* p.79

FIGURE 4.1: Comparison Between Race-specific Unemployment Rates from the Microsimulation Model Using the Best Fitted Parameter Set for the Candidacy Score and the Estimated Rates from the American Community Survey 2018 p.95

FIGURE 4.2 Comparison Between Race-gender-specific Unemployment Rates from the Microsimulation Model Using the Best Fitted Parameter Set p.96

for the Candidacy Score and the Estimated Rates from the American
Community Survey 2018

LIST OF APPENDIXES

APPENDIX 1: Psychosocial Work Environment Measures, Indexed by the 2000 Standard Occupational Classification p. 115

LIST OF ABBREAVIATIONS

ACS	American Community Survey
BIC	Bayesian Information Criteria
BMI	Body Mass Index
BLS	Bureau of Labor Economics
CARDIA	Coronary Artery Risk Development in Young Adults Study
CVD	Cardiovascular Disease
DASH	Dietary Approaches to Stop Hypertension Study
DBP	Diastolic Blood Pressure
DEI	Diversity, Equity, and Inclusion
IPUMS	Integrated Public Use Microdata Series
JNC-7	The Seventh Joint National Committee on Prevention, Detection, Evaluation, and Treatment of Hypertension guideline
LPN	License Practical Nurse
MPR	Medication Adherence Rate
NHANES	National Health and Nutrition Examination Survey
NHIS	National Health Interview Survey
OCC	US Census Occupational Classification
OEWS	Occupational Employment and Wage Statistics
O*Net	Occupational Informational Network Database
PWE	Psychosocial Work Environment
RN	Registered Nurse
SBP	Systolic Blood Pressure
SOC	Standard Occupational Code
STM	State Transition Model

US	United States

CHAPTER 1

DISSERTATION INTRODUCTION

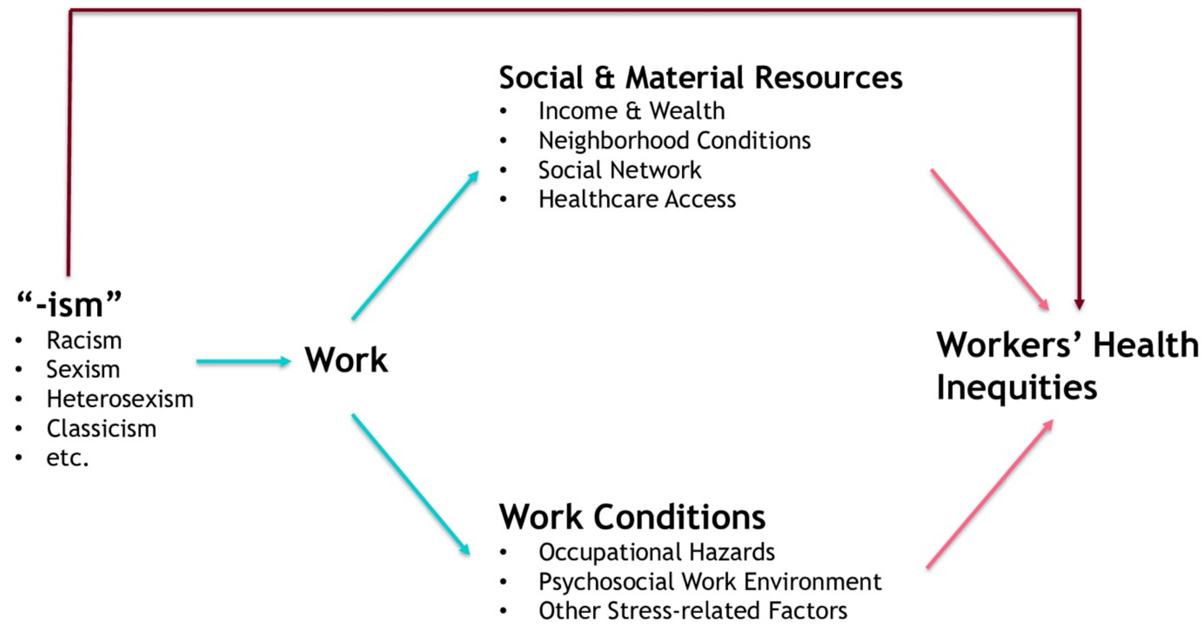
Health inequities between Black and White Americans have persisted for as long as the data have been collected. However, during the COVID-19 pandemic, the evidence of these inequities has been brought to the spotlight, especially those between Black and White workers. (Y.-H. Chen et al., 2021; Hawkins, 2020; Matthay, Duchowny, Riley, & Galea, 2021; Reitsma et al., 2021) Based on the 2019 Current Population Survey analysis, Black workers are more likely to work in essential industries such as healthcare, social assistance, or meat processing than White workers. Black workers are also more like to work in occupations with frequent exposure to infections or those that required workers to be near one another, increasing their risk of COVID-19 infection.(Hawkins, 2020)

These differential exposures to occupational health risks and workers' health inequities call scholars' and policymakers' attention to critically examine the role of work as a social determinant of health and to the fact that race patterns the likelihood of exposure to occupational health risks. (Ahonen, Fujishiro, Cunningham, & Flynn, 2018; Lipscomb, Loomis, Mcdonald, Argue, & Wing, 2006) To many scholars, work is synonymous with employment status. Although an ability to get and maintain work does affect workers' health, the nature of the work – which can be predicted by the industry ones work in, their occupation, and their position in the organizational hierarchy – also have a significant impact on workers' health trajectories.

For example, the inverse hazard law explains the relationship between the occupational class of the worker and the pattern of disease exposure. (Krieger et al., 2008) This theory characterizes exposure to occupational health risk to be inversely linked to workers' power, that can be proxied by their occupational status in the occupational hierarchy. High-status workers are those with high education and high skill. They receive high wages and can muster resources to avoid exposure to occupational hazards. They also face a lower risk of job loss and are less likely to lose access to health-promoting resources than low-status workers. In addition, although high-status workers tend to have a higher job demand, their job tends to offer higher levels of control over what, when, and how they conduct their tasks, which further minimizing work-related stress that could have negatively affected their health.

Figure 1.1 display the social production of workers' health inequities framework, proposed by Ana Diez Roux in 2020. Because work influences health status through access to social and material resources as well as patterns the exposure to high-risk work conditions, systems of oppression such as structural racism, sexism, classism, and many other -isms, that hinder the ability of Black workers to enter certain classes of work are the fundamental cause of racial health inequities.(Phelan & Link, 2015) These -isms can also act as stressors themselves. Black workers embody multiple forms of oppression. Being constantly in the state of hypervigilance and being chronically exposed to stress hormones, Black workers "weather" greater wear and tear to their bodies, making them more vulnerable to poor health than their White peers.(Geronimus, 1992)

FIGURE 1.1 Social Production of Workers' Health Inequities Framework



Note: Adapted from Diez Roux AV. (2020). Conceptual and Methodological Considerations in Identifying the Contribution of Work to Health Disparities. NIMHD Workshop on the Role of Work in Health Disparities in the United States.

Traditionally, when we think about policies to eliminate health inequities among workers, we often focus on redesigning jobs or changing workplace environments to minimize occupational health risks. (Ahonen et al., 2018; Lipscomb et al., 2006)The best example is an initiative to increase the supply and access to personal protective equipment (PPE) during the COVID-19 pandemic.(Occupational Safety and Health Administration, 2021) Furthermore, we also focus a great deal on improving access to and utilization of health services among Black workers. (Yearby, 2018) These two types of interventions address the relationships shown in Figure 1.1 with the pink arrows. Although these interventions are critical to improving workers' health, they may not close the racial health gaps. Hence, my goal is to improve the literature by examining the extent to which interventions addressing the blue arrows in Figure 1.1 contribute to eliminating workers' health inequities. To do so, I used microsimulations, which is a method commonly used by decision scientists.

Microsimulations are computer models that allow researchers to observe population-level patterns that emerge among heterogenous *synthetic* individuals. (Luke & Stamatakis, 2012; Macy & Willer, 2002) Microsimulations are alternatives to randomized controlled trials (RCTs). (Marshall & Galea, 2015) In typical RCTs, researchers recruit a group of participants, separate them randomly into a treatment and a control group and assess the effectiveness of an intervention by comparing the health trajectories of these two groups. For microsimulation studies, in contrast, no participant recruitment is conducted. Instead, researchers use a computer program to simulate a cohort of people with similar characteristics as their population of interest. The whole simulated cohort first serves as a control group. Researchers document their health trajectories under the "controlled" condition. Next, this same cohort (all participants) is assigned by researchers to receive the treatments of interest. Their health trajectories under the experimental conditions are compared to those documented under the controlled condition earlier. Given the key advantages for microsimulation studies include 1) an ability to bypassing the recruitment stage, which, for most RCTs, is the most expensive stage, and 2) an ability to examine the impacts of interventions that may be difficult to implement (e.g., assigning a life-saving treatment to one group and preventing another group from accessing it entirely) or even unethical to do (e.g., assigning participants to live in poverty), microsimulations have been utilized extensively by health services and policy researchers in the past decades for healthcare technology and policy evaluation. (Siebert, Alagoz, Bayoumi, Jahn, Owens, Cohen, & Kuntz, 2012)

My dissertation applied this approach to examine the extent to which the elimination of work inequity and occupational segregation in the workforce contributes to closing the racial gap in workers' health. For this demonstration project, I used hypertension among healthcare workers as a case study. Hypertension is one of the highly prevalent chronic cardiovascular conditions among the US healthcare workforces. Hypertensive workers face increased risks of cardiovascular diseases and preventable death. They also incur about $2000 more of healthcare expenses compared to healthy workers.(Kirkland et al., 2018)

This dissertation has three main chapters. In Chapter 2, I derived the hypertension risk equations that incorporate the psychosocial work environment (including job demand, job control, and support) as key hypertension risk predictors. These equations are the ingredients for the microsimulation model described in the following chapter to predict hypertension among the Black and White healthcare workforces. Besides deriving the equations, I also tested whether the hypertension risk equations that include psychosocial work environment can predict hypertension onset more accurately than the equations that do not include these factors.

In Chapter 3, I described the development of a microsimulation that tracks employment status, psychosocial work environment, health behaviors, and hypertension status among the occupationally segregated simulated Black and White healthcare cohorts from age 25 to 64 (referred to as the "status-quo" model). To examine the extent to which racial inequity in hypertension narrow when Black and White workers can access occupations similarly, I modified the model structure four different ways and documented the 40-year prevalence difference between these experimental conditions and the status-quo condition.

In Chapter 4, I described my effort to convert the cohort-based model into a population-based model. To use microsimulations to evaluate policy impact, researchers must first make sure that their status-quo model can replicate trends occurring in the real world. This is done by comparing simulation outputs with empirical data. However, cohort-based data for the healthcare workforce used for model validation is limited, but population-based surveillance data is more readily available. Converting a cohort- to a population-based model in completion is beyond the scope of this dissertation. As an initial effort, I conceptualized a population job-matching algorithm and searched for model parameters that allow the algorithm to closely match the empirical unemployment rates of the Black and White healthcare workforces. I scoped this project by focusing on healthcare aides working in the Chicago area only. At the conclusion of Chapter 4, I also discussed potential next steps that I can take during my postdoctoral training to complete the population-based model and use it to examine the racial equity impacts of workforce desegregation interventions.

The studies described in this dissertation was reviewed and designated as non-human research by the Institutional Review Board of the University of Minnesota. The contents of Chapter 2 and 3 are organized like manuscripts ready for journal submission.

CHAPTER 2

PREDICTING THE ONSET OF HYPERTENSION FOR WORKERS: DOES INCLUDING WORK CHARACTERISTICS IMPROVE RISK PREDICTIVE ACCURACY?

2.1 ABSTRACT

Despite extensive evidence of work as a key social determinant of hypertension, risk prediction equations incorporating this information are lacking. Such limitations hinder clinicians' ability to tailor patient care and comprehensively address hypertension risk factors. This study examined whether including work characteristics in hypertension risk equations improves their predictive accuracy. Using occupation ratings from the Occupational Information Network database, we measured job demand, job control, and supportiveness of supervisors and coworkers for occupations in the United States economy. We linked these occupation-based measures with the employment status and health data of participants in the Coronary Artery Risk Development in Young Adults (CARDIA) study. We fit logistic regression equations to estimate the probability of hypertension onset in five years among CARDIA participants with and without variables reflecting work characteristics. Based on the Harrell's c- and Hosmer-Lemeshow's goodness-of-fit statistics, we found that our logistic regression models that include work characteristics predict hypertension onset more accurately than those that do not incorporate these variables. We also found that the models that rely on occupation-based measures predict hypertension onset more accurately for white than Black participants, even after accounting for a sample size difference. Including other aspects of work, such as workers' experience in the workplace, and other social determinants of health in risk equations may eliminate this discrepancy. Overall, our study showed that clinicians should examine their patients' work-related characteristics to tailor hypertension care plans appropriately.

2.2 INTRODUCTION

2.2.1 Predicting Hypertension Onset: The Current Practice

Risk equations are essential tools that guide clinicians' decisions about which health services to use or preventative strategies to recommend when caring for patients. At least 48 different hypertension risk equations have been developed to date.(Sun et al., 2017) The utility of risk equations depends not only on their predictive accuracy but also their usability. In general, predictive accuracy means two things: 1) the degree to which risk equations can accurately distinguish between people who will have or not have a disease (i.e., a measure of discrimination) and 2) whether they can predict disease for people at different levels of risk (i.e., a measure of calibration).(Cook, 2007) Input variables for risk equations should also be readily available to clinicians (e.g., information collected during a regular office visit and stored in medical records). The vast majority of the existing hypertension risk equations predict disease onset based on age, sex, current blood pressure (often systolic blood pressure or prehypertensive/high-normal status), body mass index (BMI), smoking status, exercise, and family history;(Sun et al., 2017) in other words, demographic, behavioral, and non-invasive biomarker data. Another characteristic of risk equations that clinicians often overlook is whether the equations predict a disease equally well for people from different social groups. In recent years, the lack of attention to this characteristic has been highlighted by several empirical studies demonstrating that the disease status of Black patients can be systematically misclassified if a race variable (i.e., a socially constructed characteristic)(Smedley & Smedley, 2005) is embedded in risk equations to adjust for unexplained risk differences between Black and white patients.(Roberts, 2020) Using a race-correction term to predict patients' health trajectory without considering health-harming effects of racism and differences in social needs and social determinant of health deprives unhealthy Black patients from access to entitled health services and compensation.(Kakani, Chandra, Mullainathan, & Ziad, 2020; McClure, Vasudevan, Bailey, Patel, & Robinson, 2020) This evidence of inequitable care led to calls to remove a race-correction term from risk equations and other aspects of clinical practices.(Roberts, 2020; Vyas, Eisenstein, & Jones, 2020)

2.2.2 Work as a Social Determinant of Hypertension

The work we do affects our risk of hypertension. Three occupational determinants of hypertension have been extensively researched in the past few decades: job insecurity, job loss, and the psychosocial work environment. Job insecurity and job loss, which are predictable by workers' occupations,(Burgard, Brand, & House, 2009) increase the risk of hypertension among workers directly as added sources of stress and indirectly by disrupting access to essential health-promoting resources (e.g., income, healthcare coverage). Studies from both the United States (US) and Scandinavian countries show that workers who have experienced job insecurity or job loss are more likely to be hypertensive than those who have not,(Acevedo, Mora-Urda, & Montero, 2019; Levenstein, Smith, & Kaplan, 2001; Nygren, Hammarström, & Gong, 2015). The degree to which these risk factors affect workers' blood pressure varies based on the workers' gender, age when job loss occurs, and the duration of unemployment.(Acevedo et al., 2019; Levenstein et al., 2001; Nygren et al., 2015)

The nature of work and the workplace also predict the onset. Well-documented evidence shows that exposure to work-related psychosocial stressors, also referred to as psychosocial work environment (PWE), predicts high stress and increases the risk of hypertension.(Gilbert-Ouimet, Trudel, Brisson, Milot, & Vézina, 2014) Three dimensions of PWE predict hypertension onset among workers: job demand, job control, and work-related support.(Johnson & Hall, 1988; R. A. Karasek, 1979) Job demand is characterized by the worker's workload, time pressure, and role conflict. Job control is characterized by the worker's ability to control his/her work activities. This dimension of the PWE consists of two subcomponents: 1) skill discretion (levels of skill and creativity required on the job and the flexibility an employee is permitted in deciding what skills to use); and 2) and decision authority (opportunities for workers to make decisions about their work). The third PWE dimension, work-related support, is characterized by levels of social interaction and support received from coworkers and supervisors. Workers whose occupation is associated with high job demand, low job control, and have limited support face an increased risk of hypertension onset compared to workers whose occupation is low in job demand, high in job control, and receive extensive support.(Johnson & Hall, 1988; R. A. Karasek, 1979)

2.2.3 Current Study

Despite strong evidence that work characteristics predict the onset of hypertension, no existing risk equations account for these variables. This oversight may represent a missed opportunity for clinicians to better identify patients at high risk of hypertension onset. The lack of risk equations that account for work characteristics also hinders clinicians' ability to look beyond their clinic walls to address a root cause of hypertension inequities in the community they serve. The objective of our study is to examine the extent to which including job loss/job insecurity (measured by employment status) and PWE (measured by the occupation-based measures derived from the publicly available occupation rating data) improve the accuracy of the prediction of hypertension onset for patients or not. We purposefully excluded a risk-correction term from our risk equations and evaluated factors that are the root cause of racial inequity in hypertension instead.

2.3 MATERIALS AND METHODS

2.3.1 Data

Our analysis used the public data from the Coronary Artery Risk Development in Young Adults (CARDIA) – a multi-center prospective study designed to assess exposure to cardiovascular risk factors in young adulthood and patterns of health outcomes in later life. Detailed descriptions of the study design and data collection procedures are published elsewhere.(Friedman et al., 1988) In this secondary analysis, we used participants' work characteristics and relevant hypertension risk factors data from the follow-up assessment conducted in 2000 (Year 15) to predict their hypertension onset in 2005 (Year 20).

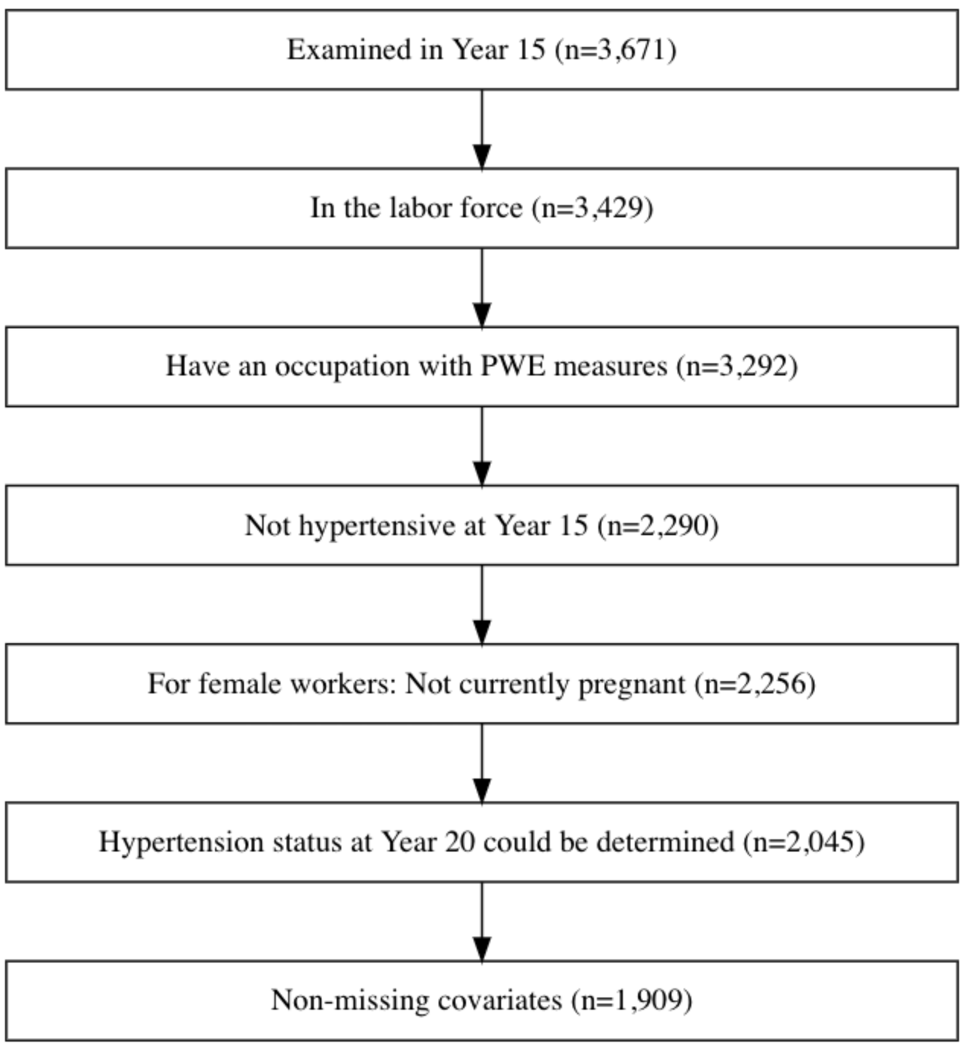
CARDIA collected data on a host of cardiovascular risk factors. At all assessments, certified technicians measured the blood pressure of the participants. The systolic (SBP) and diastolic blood pressure (DBP) were measured three times from the participant's right arm using the Hawksley random-zero sphygmomanometer (Year 15) and the Omron HEM907XL machine (Year 20). We examined non-work-related risk factors as suggested by the current literature.(Benjamin et al., 2018a) Primary risk factors consisted of each participant's age, gender (male; female), educational attainment (less than high school, some college to having a college degree; higher than college), parental history of hypertension, BMI, and diagnoses of health conditions that are positively associated with hypertension, including high cholesterol, diabetes (type 1 or type 2), heart problems (e.g., heart attack, angina, rheumatic heart disease, mitral valve prolapse), and kidney problems (e.g., urine infection from kidney, kidney stone, kidney problems like nephritis or glomerulonephritis, kidney failure, dialysis, or a kidney transplant). We also included participants' insurance coverage at the Year 15 assessment, as individuals who have difficulty accessing healthcare when needed are less likely to be in control of blood pressure and other conditions co-occurring with hypertension (e.g., diabetes).(Kressin et al., 2020) Lastly, we also included three health behaviors that are associated with hypertension:(Benjamin et al., 2018a) drinking status (current drinker; not current drinker), smoking (never smoker, former smoker, current smoker), and physical inactivity during the past year compared to people with the same gender and age (physically inactive; physically active).

As for work-related characteristics, CARDIA assigned participants the 3-digit 1990 US Census Occupational Classification (OCC) based on their response to questions about their industry of employment, occupation, and a class of worker. To determine employment status, participants were asked to describe their current main daily activities and/or responsibilities, with possible responses including working full-time, working part-time, being unemployed/laid off, looking for work, and housekeeping or raising children full time. To assess PWE for workers in our study, we derived the occupation-based measures using the occupation rating data from the Occupational Information Network (O*Net) database.(O*NET Resource Center, 2019) This publicly available online database contains ratings of over 200 occupational characteristics from approximately 900 occupations in the US economy. Ratings of occupational tasks, work activities, knowledge, education and training, work styles, and work context are based on questionnaires completed by a representative sample of current job incumbents. Trained occupational analysts also provide ratings on skills required for particular occupations and how important all rated characteristics are to the success of specific occupations. Since 2005, the O*Net data have been used in more than 60 published studies to examine the extent to which various work-related exposures predict workers' health status. We used similar O*Net items as in previous studies to derive the job demand, job control, and support measures.(Cifuentes et al., 2007; McCluney, Schmitz, Hicken, & Sonnega, 2018) The possible range is 0-4 for the job demand and job control measures and 0-2 for the support measure, with higher scores indicating greater extent. For a description of the development process of our PWE measures and how we mapped these measures to the CARDIA data, please refer to supplements 2.1 and 2.2, respectively. For the PWE values associated with specific occupations, please refer to appendix A1.

2.3.2 Exclusion Criteria

The total number of participants who received an assessment in Year 15 was 3,671. We restricted our analytical sample to participants with non-military occupations who reported working full-time, part-time, and unemployed, laid off, or actively looking for jobs in Year 15. Participants were excluded if they worked in occupations to which the PWE measures could not be assigned (see Table S2.1), if they were hypertensive or had a history of hypertension before Year 15, were pregnant at the time of the assessment (women only), had a missing hypertension status in Year 20, or had missing covariates described above. Figure 2.1 displays the number of excluded participants in each exclusion step to arrive at the final analytical sample (N=1,909). The age, gender, and educational makeup of our final analytical sample were not significantly different from the excluded group. However, the proportion of Black participants in our analytical sample was significantly smaller than those in the excluded group (37.4% vs. 54.3%, $p<0.001$).

FIGURE 2.1: Sample Exclusion



2.3.3 Model Estimation and Validation

We defined hypertension as having SBP ≥ 140 mmHg, DBP ≥ 90 mmHg, and/or if the participant was taking hypertensive medication, consistent with the Seventh Report of Joint National Committee on Prevention, Detection, Evaluation, and Treatment of Hypertension guideline (JNC-7).(Chobanian et al., 2003) Participants with pre-hypertension were those with SBP of 120 to 139 mmHg and/or DBP of 80 to 89 mmHg.(Chobanian et al., 2003) We fitted a logistic regression to estimate a five-year probability of hypertension. Similar to other US-based models,(Kshirsagar et al., 2010; Parikh et al., 2008; Paynter et al., 2009) we minimized the use of interaction terms in our models. We tested 2-way interactions between the three PWE measures with gender and age groups, grounded on the evidence that these demographic characteristics likely affect ones' experience in the workplace.(McCluney et al., 2018) We employed a backward selection algorithm to arrive at the most parsimonious model. For each round of deletion, the algorithm calculated the Bayesian Information Criterion (BIC), which combines the model likelihood with a penalty for the number of predictors in the model;(Neath & Cavanaugh, 2012) the model with the lowest BIC was considered the most parsimonious model. To ensure that the final model reasonably predicted hypertension among workers and takes into consideration the employment status and PWE, we purposefully programmed the selection algorithm to generate several models: 1) retained variables that were significantly associated with the five-year probability of hypertension (simplified model); 2) retained significant variables *and* employment status and all three dimensions of PWE regardless of their p-value (full PWE model); and 3) retained significant variables, employment status, and then only those PWE dimension that were significantly associated with hypertension (partial PWE model). For each PWE model, we also tested whether retaining participants' gender and age on top of the work-related variables further improve the model's performance or not.

We validated our models using two metrics. Model discrimination was evaluated using the Harrell c-statistic; predictive models with a c-statistic of 0.7 or higher are typically considered to have good discrimination.(Hosmer, Lemeshow, & Sturdivant, 2000) Model calibration was evaluated using the Hosmer-Lemeshow goodness-of-fit statistic, which is distributed as chi-squared. A statistically significant result for the goodness-of-fit test indicates that there is a statistically significant difference in the predicted number of outcomes compared to the observed number of outcomes for at least one group (i.e., poor calibration).

2.3.4 Comparison of Model Prediction Accuracy for Black and White Participants

We compared the c-statistics evaluated for the Black participants only and white participants only. Because our analytical sample contained an unequal number of Black (n=733) and white (n=1,176) participants, this sample size difference may contribute to differences in model prediction accuracy between these groups. We, therefore, created 200 datasets of white participants of the same sample size as that of Black participants (i.e., n=733) by sampling without replacement from the original sample of white participants. We then repeated the estimation process described above for the combined Black and white samples (total n=1,466 for each dataset). The mean of the c-statistics estimated for white participants based on all 200 samples was compared to the c-statistic evaluated using the full sample of Black participants with two-sample T-tests.

All data management and analyses were conducted in R version 3.5.2. The Institutional Review Board of the University of Minnesota reviewed this study protocol and designated it as non-human research.

2.4 RESULTS

Table 2.1 displays the characteristics and hypertension status of participants in our sample. After applying the exclusion criteria, our sample consisted of 1,909 participants with a mean age of 40.3 years that were relatively balanced in sex (54% female and 46 % male) but unbalanced in race (38% Black and 62% White). A large majority of the participants in our sample worked full-time (81%) or part-time (12%). The mean job demand, job control, and support scores were 1.8 (SD=0.3), 2.7 (SD=0.6), 1.2 (SD=0.2), respectively. Overall, the participants were generally healthy, with a mean BMI of 27.9 and prevalence of hypertension co-occurring conditions lower than the national average.(National Institute for Occupational Safety and Health, 2019) Most participants reported drinking alcohol, never smoke, and being physically active. At Year 20, 11.3% of participants who were hypertension-free at Year 15 developed hypertension.

TABLE 2.1: Analytical Sample Characteristics at Year 15 and Their Hypertension Status at Year 20 (n=1,909)

	Frequency	Percent
Sociodemographic Characteristics		
Age (Mean, SD)	40.3	(3.6)
Black	733	(38.4%)
Female	1031	(54.0%)
Less than high school	343	(18.0%)
Some college to college degree	1070	(56.1%)
Higher than college	496	(26.0%)
Insurance Coverage		
Employer-sponsored	1575	(82.5%)
Medicaid/Medicare	80	(4.2%)
Military insurance	27	(1.4%)
Self-insured	211	(11.1%)
Uninsured	1	(0.1%)
Health Conditions		
Body mass index (Mean, SD)	27.9	(6.0)
High cholesterol	305	(16.0%)
Heart problem	201	(10.5%)
Diabetes	69	(3.6%)
Kidney problem	112	(5.9%)
Health Behaviors		
Drinker	1572	(82.3%)
Never smoker	1209	(63.3%)
Former smoker	353	(18.5%)
Current smoker	347	(18.2%)
Physically inactive	103	(5.4%)
Employment Status		

Work full time	1548	(81.1%)
Work part time	231	(12.1%)
Unemployed/Looking for work	130	(6.8%)
Psychosocial Work Environment (Mean, SD)		
Job demand (0-4)	1.8	(0.3)
Job control (0-4)	2.7	(0.6)
Job support (0-2)	1.2	(0.2)
Hypertension History and Status		
Have at least one parent with hypertension*	1290	(67.6%)
Prehypertension† - Year 15	504	(26.4%)
Hypertension‡ - Year 20	215	(11.3%)

Notes:
* At least one parent or both parents with history of hypertension
† Prehypertension: SBP 120-139 mmHg or DBP 80-89 mmHg
‡ Hypertension: SBP≥ 140mmHg or DBP≥ 90mmHg or currently taking hypertension medication

Table 2.2 displays the parsimonious models with the lowest BIC based for the five backward selection strategies. When no restriction was imposed on the selection (simplified model), the backward selection identified the logarithm of the BMI, being a current smoker, being prehypertensive, and having a family history of hypertension as predictors of hypertension onset in the next five years. When we purposefully programmed the selection algorithm to retain employment status and all three dimensions of the PWE (full PWE model), all predictors identified in the simplified model remained significant in this model. Levels of job control associated with the worker's occupation was the only PWE dimension that predicted hypertension onset in five years with $p<0.05$. When participant's gender and age were also retained (full PWE model with gender and age), the coefficients of the predictors changed slightly compared to in the full PWE model. When we purposefully programmed the selection algorithm to retain only employment status and job control (partial PWE model), the final model identified the same set of predictors as in the full PWE model. The addition of gender and age (partial PWE model with gender and age) did not change the effect size of the model predictors significantly. All five models described earlier had high discrimination (greater than 0.8) and were well-calibrated. The full PWE model with gender and age, the partial PWE model, and the partial PWE model with gender and age had the highest c-statistics (0.805), but the simpler full PWE predicts hypertension onset almost equally well (c-statistic=0.804) with slightly better calibration (Hosmer-Lemeshow $\chi 2=6.09$).

TABLE 2.2: Logistic Regression Models Predicting Five-year Hypertension Onset and Their Validation Statistics

Predictor	Simplified			Full PWE			Full PWE with Gender and Age			Partial PWE			Partial PWE with Gender and Age		
	Coeff	SE		Coeff	SE		Coeff	SE		Coeff	SE		Coeff	SE	
Model Estimation															
Intercept	-12.24	1.29	***	-11.13	1.71	***	-12.07	1.99	***	-11.13	1.38	***	-12.07	1.68	***
Log BMI	2.619	0.38	***	2.556	0.38	***	2.497	0.38	***	2.55	0.38	***	2.496	0.38	***
Current smoker	0.836	0.18	***	0.761	0.18	***	0.775	0.18	***	0.757	0.18	***	0.77	0.18	***
Currently prehypertensive†	0.662	0.19	***	1.681	0.16	***	1.71	0.16	***	1.677	0.16	***	1.706	0.16	***
Family history of hypertension‡	1.667	0.16	***	0.675	0.19	***	0.656	0.19	***	0.668	0.19	***	0.65	0.19	***
Work full time				-0.077	0.31		-0.059	0.31		-0.084	0.31		-0.067	0.31	
Work part time				-0.11	0.38		-0.135	0.38		-0.115	0.38		-0.141	0.38	
Job demand score (0-4)				0.157	0.3		0.167	0.3							
Job control score (0-4)				-0.344	0.17	*	-0.347	0.17	*	-0.301	0.13	*	-0.306	0.13	*
Support score (0-2)				-0.178	0.61		-0.16	0.62							
Age							0.024	0.02					0.025	0.02	
Female							0.197	0.17					0.188	0.17	
Model Validation															
C-statistic			0.802			0.804			0.805			0.805			0.805
Hosmer-Lemeshow $\chi 2$			8.449			6.090			9.176			8.539			10.317
Hosmer-Lemeshow *p*-value			0.391			0.637			0.328			0.383			0.243

Notes:

***: p<0.001; **: p<0.01, *: p<0.05,
† Prehypertension: SBP 120-139 mmHg or DBP 80-89 mmHg,

‡ At least one parent or both parents with history of hypertension

Table 2.3 displays the mean c-statistics of the five models evaluated with 200 datasets with all Black and equal number of sampled white participants. All models predicted hypertension well for both Black and white participants, as indicated by c-statistics of greater than 0.7. We observed significantly lower c-statistics when using data of Black participants compared to using data of sampled white participants in all models. This finding suggests that even when the prediction models are estimated using the same number of Black and white participants, our models predict hypertension less accurately for Black participants.

TABLE 2.3: Comparison of the Mean C-statistics of the 200 Regression Models Estimated Using the Datasets That Consisted of All Black Participants (n=733) and the Same Number of Randomly Sampled White Participants (n=733)†

Model	Race of the Participant	Mean C-statistic
Simplified***	White	0.818
	Black	0.762
Full PWE***	White	0.817
	Black	0.761
Full PWE with gender and age***	White	0.819
	Black	0.763
Partial PWE***	White	0.819
	Black	0.760
Partial PWE with gender and age***	White	0.815
	Black	0.763

Notes:
† p-values were based on the two-sample Student's t test comparing the mean c-statistics for the best fitted models estimated from 200 samples.

***: $p<0.001$; **: $p<0.01$, *: $p<0.05$

2.5 DISCUSSION

Our study investigated whether including employment status (as a proxy of job loss and instability) and psychosocial work environment in risk equations improves the accuracy of prediction of the short-term onset of hypertension or not. Despite work-related risk factors' direct and indirect linkages with health and well-being, clinicians have never used such information to identify patients at elevated risk of hypertension. Unlike biomedical indicators (e.g., age, weight, height) or health behaviors routinely assessed during clinical intake (e.g., smoking, drinking, physical activity), consideration of work characteristics is only possible if a patient volunteers such information to their provider. As clinicians start to look beyond the walls of their clinics and collect data on social conditions that may affect their patients' hypertension status,(Daniel, Bornstein, & Kane, 2018) our study provides new insight into how this information can help improve hypertension care. We found that risk equations that incorporate workers' biomedical risk factors as well as employment status and PWE predict the onset of hypertension more accurately than ones that use only biomedical risk factors. However, we also found that our enhanced risk equations predict hypertension onset more accurately for white than Black workers, even when the data used to derive such equation consists of the same number of data points from the two racial groups.

One of the major barriers to using work characteristics to predict disease onset is ensuring that such information is collected appropriately. While asking patients about their employment status may be difficult on its own and may require better data collection strategies or linkage of data from other sources,(Cantor & Thorpe, 2018) assessing patients' psychosocial work environment during a short clinical encounter can pose another challenge. The risk equations we presented in this paper used the occupation-based measures of job demand, control, and support that can easily be coded from a patient's response about the nature of work they do. In light of the COVID-19 pandemic and the need to better surveille the health status of US workers, the National Institute of Occupational Health and Safety has released a guideline that employers and health professionals can use for occupational coding based on a response to the question "what is your occupation?".(Marovich, Mobley, & Groenewold, 2020) Compare to the 49-question Job Content Questionnaire (JCQ)(R. Karasek et al., 1998), which is used commonly by occupational health scientists to assess PWE, the implementation of occupation-based PWE measures requires significantly less time and the occupational coding process can be made automated in the electronic medical records system. Institutional initiatives to streamline the collection of patients' work-related data will ensure the effective adoption of risk equations like ours and others that may have been in development for clinicians to predict hypertension trajectory and tailor hypertension care for their patients more effectively.

It is worth noting that occupation-based PWE measures used in our models assess the *average* level of exposure to work-related stressors for a particular occupation, but not necessarily the level that a specific patient experiences.(McCluney et al., 2018) Past research suggests that workers from different racial backgrounds experience different levels of PWE, even when they have the same occupation.(Braboy Jackson, Thoits, & Taylor, 1995; McCluney et al., 2018; Wingfield, 2019; Wingfield & Wingfield, 2014) In a racist society like the US and countries with a colonial past, residential segregation and structural racism in education jointly produce the workforce in which Black workers, particularly Black women, disproportionately hold low-status occupations relative to white workers.(McClure et al., 2020) However, even Black workers holding high-status occupations experience a more stressful and challenging PWE than their white peers. These Black workers frequently report being tokenized by their white coworkers. (Wingfield & Wingfield, 2014) They are also more likely to be assigned “diversity work” and experience workplace discrimination and harassment than Black workers with low-status occupations, let alone their white coworkers.(Wingfield, 2019) Heterogeneity in the lived experience in the workplace between Black and white workers with the same occupation may explain why our risk equations incorporating occupation-based PWE predict hypertension onset less accurately for Black than white workers.

While our choice to use the occupation-based PWE measures in our hypertension risk equations had the ease of data collection and the likelihood of adoption in the fast-paced clinical setting in mind, our findings of lower prediction accuracy for Black patients signal the need for additional research on ways to utilize work-related information in the real-world clinical setting. Discrepancies in prediction accuracy by patients’ race cannot/should not be corrected with the race-correction term; while adding an interaction term between race and PWE would capture the heterogeneous *effect* of PWE on hypertension onset by race, it does not correct the fact that patients from different racial groups have different PWE experiences for a given occupation. Future research should investigate if including other individual-level measures of social conditions, particularly those that have already been captured in electronic health records (M. Chen, Tan, & Padman, 2020), will minimize discrepancies in prediction accuracy and promote equity in healthcare for patients of all backgrounds. Additionally, researchers should investigate whether the traditional JCQ can be abbreviated for a clinical intake form and evaluate whether the racial discrepancy in the prediction accuracy by race also exists in risk equations that incorporate the JCQ responses.

Our findings should be considered in light of several limitations. First, because of our relatively small sample size after exclusion, we were unable to estimate and validate our models using two separate datasets. It is possible that the validation statistics we calculated may be overly optimistic. Hence, our risk equation should be validated with data from other longitudinal cardiovascular studies. At the time of writing, this was a challenging task because although most, if not all, longitudinal studies measured participants' employment status but did not assess participants' occupations in detail, hindering the merging of occupation-based PWE measures with biomedical risk data. Second, our study defined hypertension status based on the JNC-7 guideline. Although this procedure is consistent with the standard of care around the time the study data was collected, the American Heart Association (AHA) and the American College of Cardiology (ACC) released the updated guideline in 2017 that lower the clinical threshold for hypertension to 130/80 mmHg and eliminate the pre-hypertension category altogether. We encourage future studies with data collected after the release of the AHA/ACC guideline to replicate our protocol to examine the sensitivity of our findings. Lastly, the data used to derive our risk equations came from Black and white patients only. Thus, the risk equations presented in this paper should be examined for their prediction accuracy with data from patients from other racial backgrounds before their adoption in real-world practices.

Work is an important social determinant of hypertension and should be included in the risk prediction equations. This effort will enhance clinicians' ability to make better decisions for hypertension care for patients with varied working conditions, which has the potential to address population health inequities. We demonstrated that including patients' employment status and psychosocial work environment in risk equations improves their prediction accuracy. To maximize the utility of risk equations that include social determinants of health like work conditions, we must also determine how to effectively capture this information in ways that do not disrupt a clinical workflow. It is also critical to pay attention to racial implications, big or small, that can arise when developing decision tools like risk equations and address such issues appropriately.

SUPPLEMENT 2.1: Development of the Occupation-based Measures of Psychosocial Work Environment Using the Occupational Information Network (O*Net) Data

We extracted the occupation rating data from O*Net version 3.1, released around the time the CARDIA Year 15 follow-up assessment was conducted. O*Net items were extracted to derive the occupation-based measures of *job demand*, *job control*, and *support*, consistent with the Job Demand, Control, and Support model. For the job demand and job control measures, we used the same O*Net items as Cifuentes and colleagues (2007).(Cifuentes et al., 2007) The job demand measure includes ratings of workers' ability to shift back and forth between activities/source of information, ability to concentrate on a task over a period of time without being distracted, the seriousness of the error, and the importance of being accurate in this job (Cronbach's alpha=0.69). The job control measure includes ratings of whether the job makes use of workers' abilities, ability to try out their own ideas, ability to make decisions on their own, and ability to plan their work with little supervision (Cronbach's alpha=0.96). The support measure is adapted from the work of McCluney, Schmitz, and colleagues (2018)(McCluney et al., 2018) and uses rating scales of whether workers on this job have supervisors who train their workers well and who back them up with management (Cronbach's alpha=0.78). All O*Net items mentioned above are rated from 1 to 5, except seriousness of error and importance of being accurate which are based on a 1-to-7 and 0-to-5 scale, respectively. For all items, higher scores indicate that the particular work characteristics are "more applicable" or "more important" to specific occupations. We reversed the scale for "ability to shift back and forth between activities/source of information" and "ability to concentrate on a task over a period of time without being distracted" so that higher values for all items used to derive the job demand measure were associated with increasing job demand. Scoring for all items was then standardized to range from 0 to 1, then summed up for specific PWE domains. The possible ranges for the job demand, job control, and support measure are 0 to 4, 0 to 4, and 0 to 2, respectively, with higher scores indicating the greater extent. For 266 out of 1166 occupations in O*Net version 3.1, at least one or more of the O*Net items required for the derivation of the occupation-based measures were missing because those particular characteristics were not rated. For these occupations, the PWE measures were considered missing. Lastly, to get one set of PWE measures for each Standard Occupational Classification (SOC) code, we calculated means for occupations that share the same SOC. We were able to evaluate levels of PWE for 677 SOCs in the US economy.

SUPPLEMENT 2.2: Merging the Occupation-based Psychosocial Work Environment Measures with the CARDIA Data

Because occupations of participants in the CARDIA study were classified by the 1990 Census Bureau's Occupational Code (OCC) while the occupation-based measures derived from O*Net version 3.1 were classified using the 2000 SOC, we performed three additional steps to merge the PWE measures with the health assessment data. First, the participants' 1990 OCCs and a complete list of the 2000 OCCs were converted to the standard occupational coding system proposed by Meyer and Osbourne (2005) at the US Department of Labor.(P. B. Meyer & Osborne, 2005) Second, the participants' 1990 OCCs were mapped to the 2000 OCC system via this standard coding. This cross walking was not perfect; 25 out of 335 OCCs of the participants could not be converted into the standard coding, and thus, could not be mapped to the 2000 OCC system. As a result, the PWE measures could not be assigned to participants with these OCCs. The list of these excluded occupations, with the occupation title and the associated OCC, is displayed in Table S2.1. Lastly, we mapped the 2000 OCCs to the 2000 SOC system using the OCC-to-SOC crosswalk from the National Crosswalk Service Center.("National Crosswalk Service Center – Training Module – WIDCenter," n.d.) Once the participants' occupations were classified with the SOC system, the PWE measures could be readily assigned for participants who worked full time and part-time in Year 15. For unemployed workers, we set the value to zero for all three measures.

TABLE S2.1: Occupations of CARDIA Participants in Which the PWE Measures Could Not Be Assigned, Indexed by the 1990 US Census Bureau Occupational Codes (OCC)

1990 OCC	Occupational Title
37	Management related occupations, n.e.c.
114	Biological science teachers
118	Psychology teachers
127	Engineering teachers
213	Electrical and electronic technicians
314	Stenographers
323	Information clerks, n.e.c.
346	Mail preparing and paper handling machine operators
353	Communications equipment operators, n.e.c.
387	Teachers' aides
407	Private household cleaners and servants
415	Supervisors, guards
438	Food counter, fountain and related occupations
467	Early childhood teacher's assistants
474	Horticultural specialty farmers
476	Managers, horticultural specialty farms
538	Office machine repairers
667	Tailors
689	Inspectors, testers, and graders
693	Adjusters and calibrators
735	Photoengravers and lithographers
789	Hand painting, coating, and decorating occupations
796	Production inspectors, checkers, and examiners
797	Production testers
877	Stock handlers and baggers

CHAPTER 3

OCCUPATIONAL CLASS, POWER, AND HYPERTENSION INEQUITY: THE IMPLICATION OF THE INVERSE HAZARD LAW AMONG HEALTHCARE WORKERS

3.1 ABSTRACT

In the United States (US), Black – particularly Black female – healthcare workers are more likely to hold occupations with high job demand, low job control with limited support from supervisors or coworkers, and are more vulnerable to job loss than their White counterparts. These work-related factors increase the risk of hypertension. This study examines the extent to which occupational segregation explains the persistent racial inequity in hypertension in the healthcare workforce and the potential health impact of workforce desegregation policies. We simulated a US healthcare workforce with four occupational classes: health diagnosing professionals (i.e., highest status), health treating professionals, healthcare technicians, and healthcare aides (i.e., lowest status). Our "control" model created occupational segregation by allocating 25-year-old workers to occupational classes with the race- and gender-specific probabilities estimated from the American Community Survey data. Occupational class attributes and workers' health behaviors predict their hypertension status over a 40-year career. We tracked the hypertension prevalence and the Black-White prevalence gap among the "control" cohort and the "experimental" cohort in which occupational segregation was eliminated. We found that the hypertension prevalence is consistently lower in the "experimental" cohort than in the "control" cohort. The Black-White prevalence gap became approximately one percentage-point smaller in the "experimental" compared to the "control" cohort. These findings suggest that policies designed to desegregate the healthcare workforce can reduce racial health inequities in this population. Our microsimulation may be used in

future research to compare various desegregation policies as they may have different impacts on workers' health.

3.2 INTRODUCTION

3.2.1 Work as a Determinant of Health

Work is a determinant of health and a driver of population health inequities. (Ahonen et al., 2018) A multi-faceted concept, "work" encompasses individuals' ability to get work (employment status), the type of work (occupation), the setting of work (industry), the nature of work (e.g., physicality, duration of a shift), and the workplace environment (e.g., exposure to environmental hazards and the psychosocial work environment). Because of this complexity, the mechanism underlying the social production of workers' health is often studied separately by sociologists, labor economists, and occupational health scholars from varying disciplinary perspectives. With limited integration of these perspectives, evaluating the health effects of work from policies that address distal causes (e.g., what happens during the labor force development) is challenging and a critical gap in the literature.

In this study, we used hypertension as an example of a highly prevalent chronic health condition among the US workforce to examine the extent to which occupational segregation and racialized exposure to occupational health risks contribute to hypertension inequity between Black and White workforces. Hypertension affects 27% of Black workers and 21% of White workers. (National Institute for Occupational Safety and Health, 2019) Hypertensive workers face an increased risk of cardiovascular diseases, stroke, and preventable death. (Benjamin et al., 2018b) On average, hypertensive workers incur 2.5 times higher in-patient care expenditures and spend three times as much on prescriptions than workers with normal blood pressure (normotensive). (Kirkland et al., 2018) Hypertensive workers also report more absenteeism than their healthy peers, which leads to lost productivity and affects their coworkers in team-based workplaces. (Unmuessig, Fishman, Vrijhoef, Elissen, & Grossman, 2016)

Past research has shown several ways that work influences the risk of hypertension. Work acts as a "gatekeeper" to resources needed for workers' health and well-being (e.g., wage and material resources, healthcare coverage). (Lipscomb et al., 2006) The role of work as a gatekeeper to health-promoting resources is especially evident during economic recessions. For example, during the 2007 to 2009 recession, the US unemployment rates rose from 5% to 9.5%, and the median household income dropped from $54,489 to $52,195. Approximately 3 million Americans lost employer-sponsor healthcare coverage, and there was a significant decline in US population health metrics. (Bureau of Labor Statistics, 2012; Burgard & Kalousova, 2015; Holahan, 2011; Kochhar, 2012) Unemployed workers were less likely to maintain a healthy diet, not meet recommended guidelines for physical activities, and were more likely to smoke and consume alcohol heavily during the recession, further reiterates the fact that the loss of work leads to an increased risk of hypertension. (Compton, Gfroerer, Conway, & Finger, 2014; Kwak, Berrigan, Van Domelen, Sjöström, & Hagströmer, 2016; Smed, Tetens, Lund, Holm, & Nielsen, 2017; Van Domelen et al., 2011)

Besides being a resource gatekeeper, work also acts as a stressor that affects blood pressure directly via the stress pathway. Workers who have experienced job loss and those whose jobs are unstable or precarious are more likely to report hypertension than those with stable jobs. (Benach et al., 2014; Kaur, Luckhaupt, Li, Alterman, & Calvert, 2014) Older male workers whose employer reorganized or downsized and those who reported being disciplined or demoted – an indicator of job insecurity – reported SBP 5.2 mmHg higher than their counterparts whose job was secure. (Kalil, Ziol-Guest, Hawkley, & Cacioppo, 2010) A slight lower but significant increase in SBP was also reported among female workers experiencing job insecurity. (Ferrie, Shipley, Gideon, Stansfeld, & Smith, 1998) Studies from both the US and many European counties also reported higher SBP and DBP among workers experiencing job loss than employed workers. The detrimental effect of job loss on hypertension risk varies based on the workers' gender, age when job loss occurs, and the duration of the unemployment. (Acevedo et al., 2019; Levenstein et al., 2001; Nygren et al., 2015)

However, not all work is created equal. The benefits of work on cardiovascular health are modified by the work-related stress that arises from poor working conditions and the workplace environment. Among the many dimensions of work that affect workers' hypertension risk, scholars have consistently demonstrated the linkage between work-related psychosocial stressors ("psychosocial work environment": PWE) and hypertension status. (Gilbert-Ouimet et al., 2014) PWE is characterized by job demands (workload, time pressure, and role conflict), job control (decision authority, skill discretion, and the worker's ability to control his/her work activities), and support from coworkers and superiors. (Johnson & Hall, 1988; R. A. Karasek, 1979) According to the Job Demand-Control-Support model, while workers with high job demand are more likely to experience stress/burnout, job control can promote learning and mitigates job demand's harmful effects. Workers with high-demand, low-control jobs (i.e., job strain) have an increased risk of stress-related, adverse health conditions, while those with low-demand, high-control jobs have the lowest risk. For a given level of job strain, the level of superior and coworker support further protects against the increased risk of hypertension; workers holding jobs with high demand, low control, and low support (i.e., iso-strain) face the greatest risk of hypertension. (Johnson & Hall, 1988; R. A. Karasek, 1979)

3.2.2 Power, Occupational Class, and Hypertension Inequity

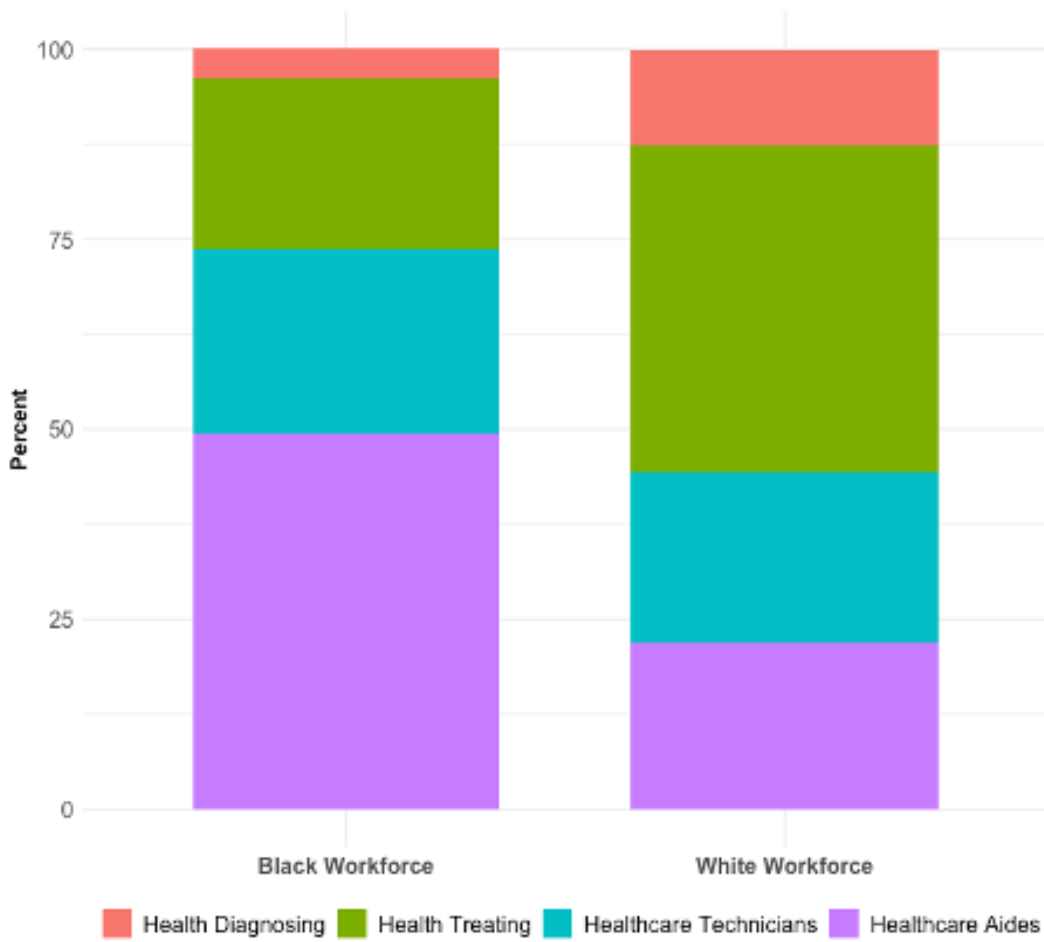
Work-related risks of hypertension are patterned by workers' occupations. (Landsbergis et al., 2015) The inverse hazard law posits that "the accumulation of health hazards tends to vary inversely with the power and resources of the populations affected." (Krieger et al., 2008) Consistent with this theory, workers in high-status occupations (i.e., having a high socioeconomic status and high earning) can muster materials and social resources to avoid exposure to health risks as well as create or influence institutional rules, policies, and practice to sustain their dominant position in the organizational hierarchy. (Budig, Hodges, & England, 2019; Krieger et al., 2008; Robinson, 2000) Early evidence of health gradients among workers by occupational class originated from the Whitehall study. Among British civil servants with the same access to government-sponsored healthcare, workers in lower employment grades were more likely to be hypertensive and had a higher mortality risk of coronary heart disease. (Marmot et al., 1991) A similar trend was also observed among US workers in many industries. For example, male aluminum manufacturing plant workers in the middle and the lowest income tertile are 20% and 4% more likely, respectively, than those in the highest income tertile to have hypertension. For female workers, the odds of hypertension for those in the middle and the lowest income tertile is 1.3 times and 1.2 times higher than those in the highest income tertile. (Clougherty, Eisen, Slade, Kawachi, & Cullen, 2011) Among healthcare workers, the prevalence of hypertension was 14% in health diagnosis professionals (e.g., doctors, dentists), 24% in health treating professionals (e.g., registered nurses, physicians assistants), 28% in healthcare technicians (e.g., laboratory technicians, dental hygienists), and 36% in healthcare aides (e.g., nursing aides, dental assistants), demonstrating the risk gradient by workers' occupational class and power within healthcare institutions. (Lee et al., 2012)

The observed hypertension gradient is attributable to the pattern of exposure to work-related risks of hypertension by occupational class. Compared to high-status workers, low-status workers face a higher threat of job loss and job insecurity. The unemployment rate for US workers in the "management, business, and financial operations occupations" is 2%. In contrast, the unemployment rates for workers in the "service occupations" and "transportation and material moving occupations" are approximately 5%. (Bureau of Labor Statistics, 2020) Increased unemployment rates by occupational class are also observed across workers within the same industry. For example, among healthcare workers, the unemployment rates among health diagnosis professionals, health treating professionals, health technologists, and healthcare aides are 1%, 1%, 3%, and 4%, respectively. (Ruggles et al., 2020) Besides the adverse health effects from job loss, low-status workers are more likely to experience iso-strain than high-status workers, the trends dated back to the 1990s in many countries. (Aust, Rugulies, Skakon, Scherzer, & Jensen, 2007; Gallo, Bogart, Vranceanu, & Walt, 2004; Joseph et al., 2016; Light, Turner, & Hinderliter, 1992; Marmot et al., 1991) Altogether, this evidence shows how a system that segregates certain groups of workers into particular occupations or occupational classes and systematically exposes these workers to a disproportionate level of hypertension risks than others is one of the fundamental drivers of hypertension inequity in the workforce.

3.2.3 The Occupational Segregation in the Healthcare Workforce and Hypertension Inequity

A highly segregated healthcare workforce mirrors racial segregation in other parts of our society, clustering Black workers, particularly Black female workers, disproportionately at the bottom of the occupational hierarchy. Figure 3.1 shows workers' distribution by occupational class for the Black and White healthcare workforces in the US in 2017 based on the American Community Survey (ACS) data. We grouped healthcare occupations using the Standard Occupational Code (SOC) into health diagnosing workers, health treating workers, healthcare technicians, and healthcare aides based on the level of education required to perform healthcare tasks. For specifics SOCs in each group, refer to supplement 3.1. Similar to many other industries, occupational segregation in the healthcare workforce is a product of two forms of oppression: structural racism (i.e., racist ideologies, policies, and practices that reinforce one another to inhibit access to economic opportunities for non-White workers) and structural sexism (i.e., "the systematic gender inequality in power and resources manifest in a given gender system"). (Bailey et al., 2017; Chung-Bridges et al., 2008; Homan, 2019) Unlike other industries, healthcare tasks are highly regulated by credentialing systems. (Duffy, 2011; Wingfield, 2019) Healthcare workers must obtain necessary formal education and professional training and pass licensing tests to enter into specific professions. Professionalization of healthcare work prevents workers from climbing up the occupational ladder as they "learn on the job," restricting interclass mobility and sustaining occupational segregation in the healthcare workforce, particularly for workers of color. (Ray, 2019)

FIGURE 3.1: Proportional Representation of Four Occupational Classes in the White and Black Healthcare Workforces



Occupational segregation in healthcare institutions likely contributes to racial health inequity in the healthcare workforce. This less discussed linkage became increasingly evidenced during the COVID-19 pandemic. Healthcare workers in close contact with infectious patients are more likely to have low wages, limited access to paid time-off, and little control of their work activities; they are also more likely to be Black. (Hawkins, 2020) For hypertension, our analysis of the National Health Interview Survey (2014-2018) shows the risk gradient was also inversely related to the occupational hierarchy. For Black healthcare workers, the prevalence of hypertension is 34%, 34%, 40%, and 40% for health diagnosing workers, health treating workers, healthcare technicians, and healthcare aides. A parallel trend was observed among White healthcare workers; however, the prevalence of all occupational classes are significantly lower compared to Black healthcare workers. Further details of this analysis are available in supplement 3.2.

3.2.4 Current Study

Integrating information from organizational and medical sociology, labor economics, and occupational health sciences literature, we used a microsimulation model to examine the extent to which occupational segregation contributes to racial inequity in hypertension in the healthcare workforce. Microsimulations integrate mathematical equations that describe biological and social processes with a system of factors that determine individuals' behaviors and health outcomes in a simulated scenario. This analytical approach allows scholars to observe population-level patterns that emerge among heterogenous *simulated* individuals and predict what may happen to them if some components of the system change. (Kaplan, 2017) We created a microsimulation that mimics the dynamics of employment status and PWE along with health behaviors to predict hypertension pathogenesis for Black and White healthcare workers across four healthcare occupational classes. Using a counterfactual scenario analysis, we examined the prevalence trends in hypertension among Black and White healthcare workforces to determine the extent to which dismantling the forces that generate occupational segregation, including structural racism and sexism, reduces the Black-White inequity in hypertension prevalence. This analysis will inform policymakers of potential implications on racial health inequities among healthcare workers resulting from implementing effective workforce desegregation policies. (Kalev, Kelly, & Dobbin, 2006)

3.3 METHODS

3.3.1 Microsimulation

We simulated healthcare workers' hypertension development and progression using a state-transition model (STM). STMs conceptualize dynamic processes (e.g., disease development) as a series of conditions ("states") and events ("transitions") that individuals experience over time. In each time step ("cycle"), individuals can move from one state to another based on some likelihood ("transition probabilities"), which can depend on an individual's characteristics. These transition probabilities are from published clinical or observational studies or are estimated from representative population data. After the population of individuals is simulated for the desired number of cycles ("time horizon"), the number of individuals in each state at each cycle are tallied to calculate disease prevalence and other outcomes of interest over time. (Siebert, Alagoz, Bayoumi, Jahn, Owens, Cohen, Kuntz, et al., 2012)

Figure 3.2 shows the dynamic process of hypertension development and progression used for our model. We tracked the hypertension status of simulated workers from age 25 (when the average US workers have attained their terminal educational degree) to the pre-retirement age of 64. In our model, one cycle represents one year. Over the workers' 40-year career, they may be in one of the five health states: *normotensive* (SBP<120 mmHg and DBP<80 mmHg), *prehypertensive* (SBP of 120-139 mmHg or DBP of 80-89 mmHg), *hypertensive* (SBP>140 mmHg, DBP>90, or being prescribed a hypertension medication), *controlled* (being hypertensive in the previous cycle but normotensive in the current cycle), and *dead*. The blood pressure thresholds used to define these states were based on the Seventh Report of the Joint National Committee on Prevention, Detection, Evaluation, and Treatment of High Blood Pressure. (Chobanian et al., 2003) Table 1 shows the data source and specific literature from where the transition probabilities used in our model were estimated or directly drawn.

FIGURE 3.2 Hypertension State Transition Diagram

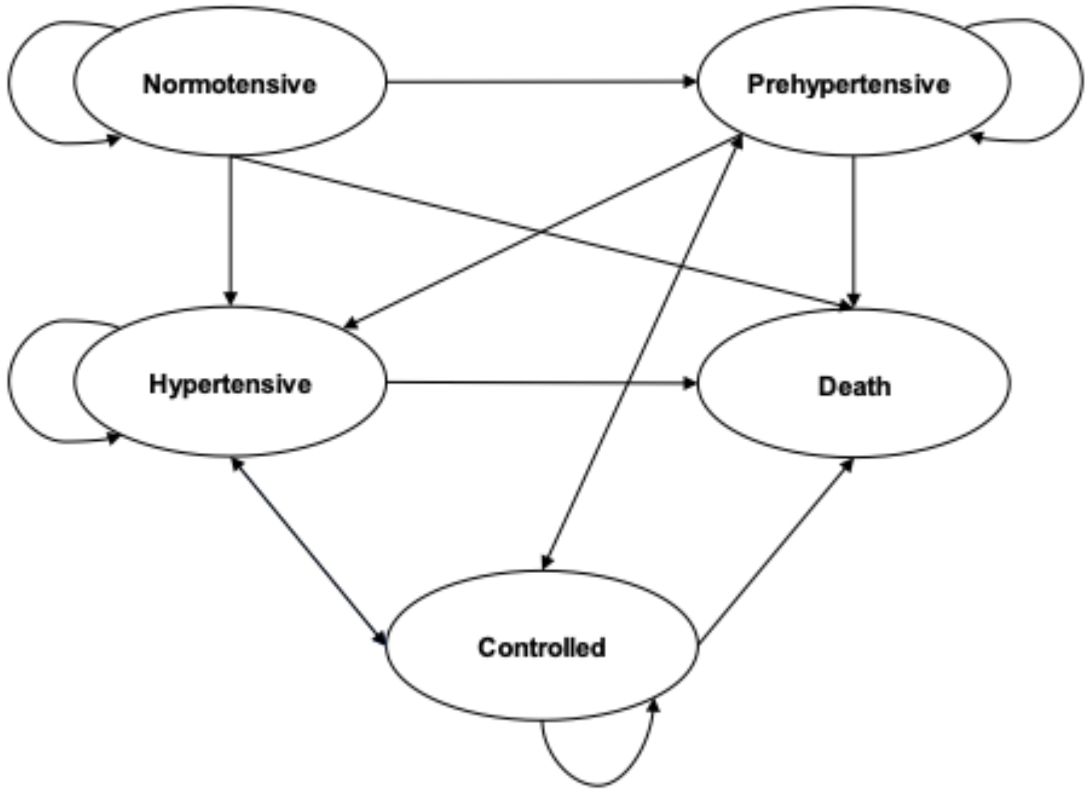


TABLE 3.1: Model Parameters

Parameter	Sample	Source
Transition probability: Normotensive -> Prehypertensive	CARDIA participants Year 15	CARDIA
Transition probability: Normotensive -> Hypertensive	CARDIA participants Year 15	CARDIA
Transition probability: Prehypertensive -> Hypertensive	CARDIA participants Year 15	CARDIA
Transition probability: Prehypertensive -> Controlled		Appel 2003
Transition probability: Hypertensive -> Controlled (by adherence level)		Bramley 2006
Probability of being prescribed hypertension medication (by race)		Samanic 2020
Probability of low, medium, high medication adherence among hypertensive individuals		Bramley 2006
Mortality rates for CVD, non-CVD, and pregnancy-related cause (by race and gender)		National Vital Statistics System 2017
Hazard ratio for CVD deaths for hypertensive individuals (by gender)		Franco 2005
Transition probability: Physically inactive <-> Physically active		Dalziel 2006
Transition probability: Never smoker -> Smoker <-> Quit (by age group: 18-29; 30-44; 45 and older)		Yi 2017
Probability of having a parental history of hypertension (by race)		Muntner 2010
Proportion of women in the healthcare workforces (by race)	Healthcare workers aged 25	ACS 2012-2017

Probability of being a current smoker, former smoker, never smoker (by race and gender)	Individuals aged 24	NHIS 2000-2018
Distribution of body mass index (by race and gender)	Individuals aged 23	NHIS 2000-2018
Probability of being normotensive, prehypertensive, and hypertensive (by race and gender)	Individuals aged 25	NHANES 1999-2018
Probability of being physically active (by race and gender)	Individuals aged 24	NHIS 2000-2018
Probability of working full-time, part-time, and unemployed (by race, gender, and occupational class)	Healthcare workers aged 25	ACS 2012-2017
Distribution of job demand, job control, and support (by occupational class)	Healthcare workers aged 25	ACS 2012-2018 linked with O*Net 3.1

We estimated the probability that workers transition to the prehypertensive and hypertensive states as a function of individual characteristics and behaviors using risk equations. Using the data from the Coronary Artery Risk Development in Young Adults (CARDIA) study, we estimated risk equations to predict the five-year disease onset for workers. (Friedman et al., 1988) Details about how we selected our analytical sample, prediction model estimation and validation approaches, and our risk equations are available in supplement 3.3. To incorporate these equations in our microsimulation model, we converted the estimated five-year probabilities to one-year probabilities using the Declining Exponential Approximation to Life Expectancy (DEALE) method. (Beck, Pauker, Gottlieb, Klein, & Kassirer, 1982) During the follow-up period in our simulation, all predictors of hypertension may change dynamically. Details about how we model these processes are available in an online supplement S4. At the end of the simulation, the model computed the prevalence of hypertension in each cycle by dividing the total number of workers in the hypertensive state by the number of workers still alive in that cycle.

3.3.2 Simulated Cohorts of Black and White Healthcare Workers

We simulated ten cohorts of 100,000 Black and 100,000 White healthcare workers for our analysis. We characterized our simulated workers by age (25 years old in the first cycle and, if alive, increased one year at the end of each cycle), gender (male; female), family history of hypertension (have at least one parent with hypertension; no family member with hypertension), body mass index (BMI; log-transformed for use in the risk equations), smoking status (current smoker; non-smoker/quit), prehypertension status, occupational class (health diagnosing workers; health treating workers; healthcare technicians; healthcare aides; see supplement S1 for the occupational classification details), employment status (work full-time; work part-time; unemployed), and the three dimension of the PWE associated with the workers' occupational class. We also characterized the workers' physical activity (physically active; physically inactive) because it is one predictor of the workers' BMI. We assigned the baseline values for each worker's characteristics using random sampling informed by the probabilities of such characteristics either among healthcare workers or a representative sample of individuals in the labor force (Table 3.1).

Our model allocated the Black and White healthcare workers to one of the four occupational classes using the predicted probabilities estimated from the ACS data (2012-2017). This process mimics how workers “choose” their occupation class given their qualifications, social identities, and occupational advantages. For a simulation of an occupationally segregated workforce (i.e., a status-quo condition), these probabilities were estimated with multinomial regression and were conditioned on the age, gender, and race of the worker (equations (1) to (3)).

$$\ln\left(\frac{\Pr(\text{health diagnosing})}{\Pr(\text{healthcare aides})}\right) = \alpha_{1a} + \beta_{1a}\text{Age} + \gamma_{1a}\text{Women} + \pi_{3a}\text{Black} \quad (1)$$

$$\ln\left(\frac{\Pr(\text{health treating})}{\Pr(\text{healthcare aides})}\right) = \alpha_{2a} + \beta_{2a}\text{Age} + \gamma_{2a}\text{Women} + \pi_{2a}\text{Black} \quad (2)$$

$$\ln\left(\frac{\Pr(\text{healthcare technicians})}{\Pr(\text{healthcare aides})}\right) = \alpha_{3a} + \beta_{3a}\text{Age} + \gamma_{3a}\text{Women} + \pi_{3a}\text{Black} \quad (3)$$

We assumed that once healthcare workers "choose" their occupational class at age 25, based on the probabilities shown in the supplement 3.5 (status quo scenario), they will remain in that class until retirement. A worker’s employment status may change between working full-time, part-time, or being unemployed throughout their career, depending on their age, gender, race, history of unemployment, and occupational class. Because there is no interclass mobility in our model, PWE levels associated with the workers' chosen occupation were assigned once at age 25 by randomly sampling from their empirical distributions for the US healthcare workers (see supplement 3.6). During the follow-up period, PWE was included to estimate transition probabilities only when the workers were employed full-time or part-time. When the workers were unemployed, the model set the exposure to PWE for that particular cycle to zero.

3.3.3 Occupational Desegregation and Hypertension Inequity

Simulation outputs from the status-quo model and those that emerged from the models in which one particular model component is modified can be treated as "control" and "experimental condition," respectively. In this analysis, we compared the hypertension prevalence trend among Black and White healthcare workers observed in the segregated workforce to the trends that emerged from four desegregation scenarios. These counterfactual scenarios differ from one another by the probabilities we used to allocate the 25-year-old Black and White workers to occupational classes (supplement 3.5, scenario A-D).

In *scenario A*, we allocated Black and White workers to occupational classes using "raceless" population average probabilities. These probabilities were estimated similarly to those from equation (1) to (3), except that we omitted race from these regressions. In this scenario, Black workers have greater access to high-status occupation classes, while White workers have greater access to low-status occupational classes relative to the status-quo scenario. However, because we did not omit gender from these regressions, men still have a better chance of entering high-status occupational classes than women. In *scenario B*, we omitted both race and gender from equation (1) to (3). The results of this estimation were "raceless and genderless" population average probabilities. Unlike in scenario A where sexism still exists, all workers in scenario B, regardless of their race and gender, can enter a given occupational class with the same probability.

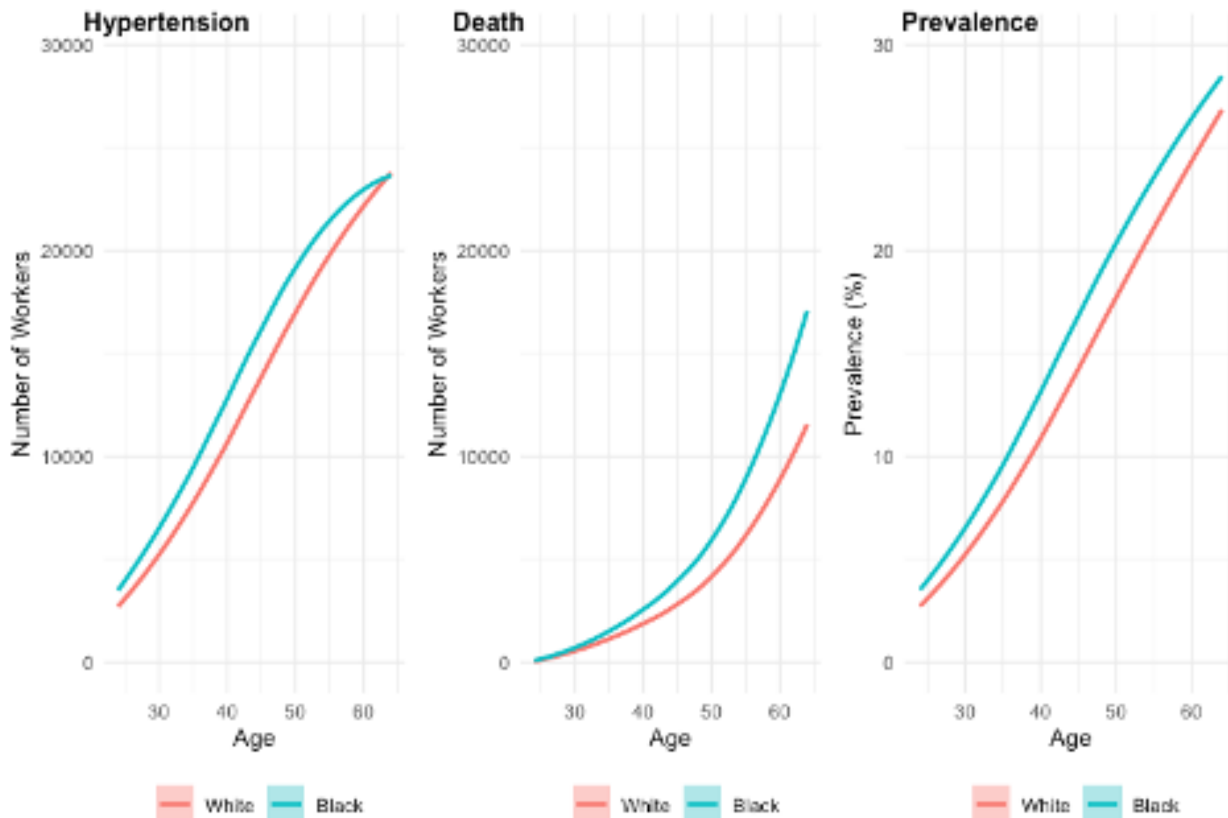
We also predicted the Black-White prevalence trends under the scenarios where improving access to high-status occupations classes for Black and female workers does not directly affect White and male workers. In *scenario C*, we set the probabilities with which Black male and Black female workers access the various occupational classes to be the same as for White male and White female workers in the status-quo scenario, respectively. In *scenario D*, we allocated all workers to occupational classes with the probabilities experienced by White men in the status-quo scenario. Since the only difference between the status-quo scenario and each of the counterfactual scenarios is how workers access their occupational class, any difference in the hypertension trends that emerged from the simulations can be attributed directly to occupational desegregation.

3.4 RESULTS

3.4.1 Status-Quo Simulation

Figure 3.3 shows the trends that emerged from our model under the status-quo condition. The observed outcomes for the Black and the White healthcare workforces are colored in cyan and red, respectively. Throughout most of the follow-up period, the number of hypertensive cases was consistently higher among the Black than the White healthcare workforces. As both workforces approached their retirement age, the number of hypertensive cases started to equalize (first panel). However, looking at the number of hypertension cases alone can be misleading. Because the death rate for the Black workers was higher than for the White workers, there were almost always fewer Black workers alive who could transition into the hypertensive state during the follow-up period than the White workers (second panel). The third panel shows the prevalence of hypertension, which was calculated as the number of hypertensive workers divided by the number of alive workers, provided a better representation of the racial inequity in hypertension among the two workforces. Specifically, the prevalence of hypertension averaging from age 25 to 64 was 14.3% for the White and 16.3% for the Black workforces.

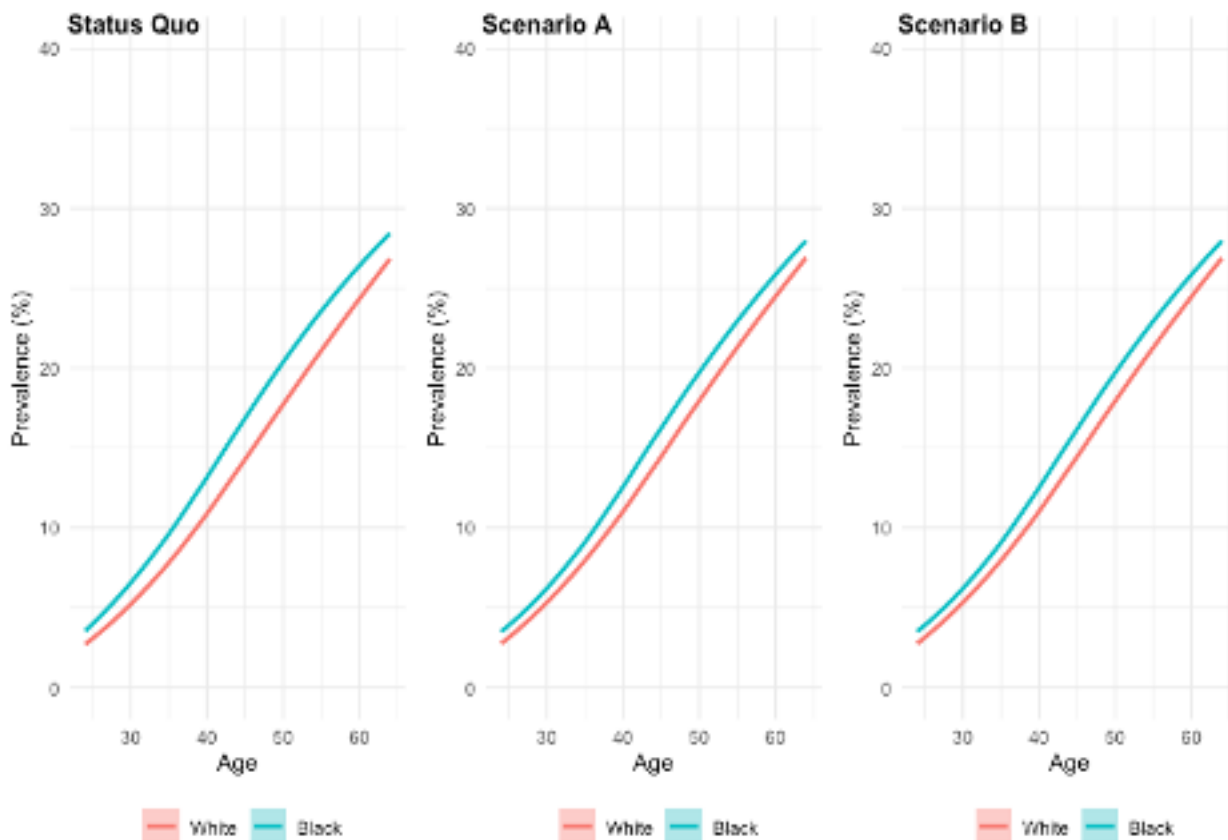
FIGURE 3.3: Status-quo Simulation Output



3.4.2 Counterfactual Scenario Simulations

Figure 3.4 shows the prevalence trends of hypertension among the Black and the White healthcare workforces for scenarios A and B, compared to the trends emerging from the status-quo simulation. When the Black and the White workers were allocated to occupational classes using the population-average probabilities, we observed the narrowing of the Black-White inequity gap in the prevalence of hypertension. In *scenario A* where gender inequity still exists, the average prevalence of hypertension was 14.4% and 15.4% for the White and the Black workforces, respectively. We observed a similar prevalence gap in *scenario B*, where both race and gender inequities were absent from the healthcare institutions. In both scenarios, the decrease in racial inequity results from the Black workers becoming healthier and the White workers facing a greater risk of hypertension.

FIGURE 3.4: Comparison of the Black-White Prevalence of Hypertension Under the Counterfactual Conditions, Scenario A & B



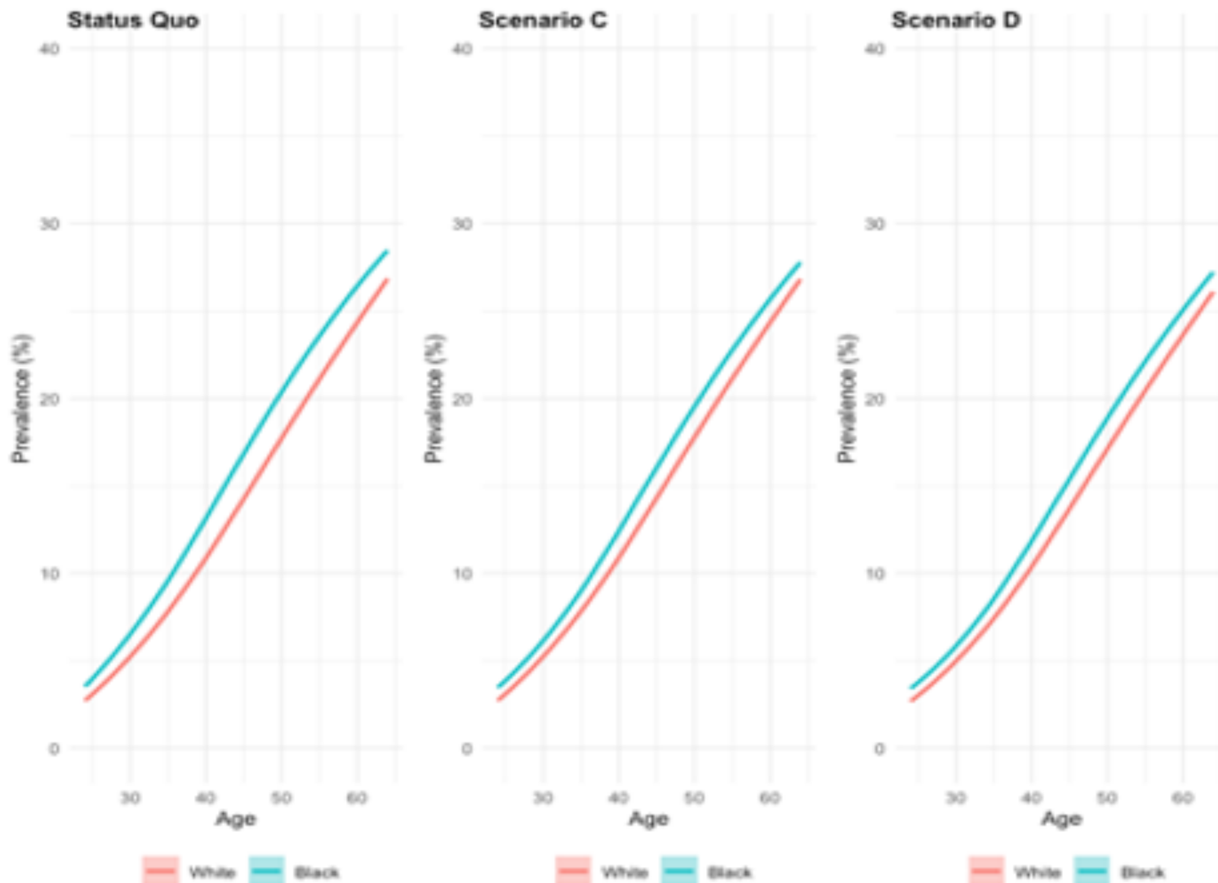
Note:

Scenario A: Improved access to high-status occupational classes for Black workers, with improved access to low-status occupational classes for White workers; gender inequity still exists.

Scenario B: Improved access to high-status occupational classes for Black workers, with improved access to low-status occupational classes for White workers; gender inequity no longer exists.

Figure 3.5 shows the prevalence trends of hypertension in the scenarios where the probabilities of entering a given occupational class for the Black workers were set equal to those of the White workers in the status quo scenario (*scenario C*). Consistent with results from the earlier scenarios, we observed the narrowing of the Black-White inequity in hypertension. However, the reduction we observed in this scenario resulted from the decreased prevalence of hypertension for the Black workforce (average prevalence of 15.6%) without changing the prevalence in the White workforce (average prevalence of 14.3%). In *scenario D*, where all the workers, regardless of their race and gender, have the same occupational class access as the White men in the status-quo condition, the average prevalence of hypertension among the Black (15.1%) and the White workforces(13.8%) decreases. The reduction in hypertension prevalence among the White workforce in this scenario is attributable to the reduction among the White female workers as they have greater access to higher-status, lower-risk occupational classes than before. The average prevalence of hypertension by age group for the status-quo and all counterfactual scenarios is available in supplement 3.7.

FIGURE 3.5: Comparison of Black-White Prevalence of Hypertension Under the Counterfactual Conditions, Scenario C & D



Note:
Scenario C: Black men access occupational classes similarly to White men in the status-quo scenario, while Black women access occupational as White women.
Scenario D: All workers access occupational classes like White men in the status-quo scenario).

3.5 DISCUSSION

The role of work as a multi-faceted driver of health inequities has received more attention from scholars in 2020 in light of the COVID-19 pandemic and the significant health risks faced by healthcare workers. (Kambhampati et al., 2020) Nevertheless, such inequities have existed for years, and the lack of resources to protect workers from diseases is only one contributing factor among many. Knowledge of how the unjust labor market mechanism – from workforce development, occupational segregation to hiring discrimination – transpires into racialized occupational health risk exposure and health inequities among workers is limited in the current literature. To address this gap, our study utilized a microsimulation model to integrate information about 1) structural racism and sexism as driving forces for occupational segregation; 2) patterns of risk exposure by occupational classes; and 3) biological and social production of workers' health. We examined the extent to which occupational segregation contributes to the persistent racial inequity in hypertension, one of the most prevalent chronic conditions among US workers. Our microsimulation experiment, which allows only occupational class access for Black and White healthcare workers at the start of their career to varying across scenarios, reveals several interesting findings.

First, we observed an approximate one-percent decrease in the average prevalence of hypertension among the Black workforce when occupational segregation is absent. This finding supports previous evidence on the adverse effects of occupational segregation on Black workers' health. (Chung-Bridges et al., 2008; J. D. Meyer, 2014) Because our microsimulation created a laboratory-like environment where "everything else" that confounds the relationship between occupational segregation and hypertension inequity is controlled for, our results were less vulnerable to unobserved biases compared to previous studies. As such, the effects we observed potentially represent a causal relationship, not just correlation. Given the estimated 1.7 million Black healthcare workers in the US and the $1,920 excess health care expenses incurred by hypertensive patients annually, (Kirkland et al., 2018) a one-percent decrease in the hypertension prevalence in the desegregated workforce could have translated into at least approximately $32 million of saving to society.

Second, we observed a decrease in hypertension among the Black workforce but an increase in hypertension among the White workforce when both groups were allocated to occupational classes using the “raceless” and “race- and genderless” probabilities relative to the status-quo condition. These are the trends we would likely observe when the structural advantages for White workers created by White supremacy are eliminated completely. White supremacy is a sociopolitical system that socially, economically, and ideologically benefits European descendants and oppresses people in other racial groups. (Malat, Mayorga-Gallo, & Williams, 2018) From White supremacy, the concept of Whiteness was formed. Whiteness refers to the normalization of White racial identity throughout America's history which has created a culture where non-White persons are seen as inferior or abnormal. (Bonilla-Silva, 2004) In *Black Reconstruction in America, 1860-1880*, W.E.B. Du Bois coined the term “wage of Whiteness” to characterize psychological benefits that the White working-class received because of their racial status in a racialized society. (Du Bois, 1998) He stated, “It must be remembered that the White group of laborers, while they received a low wage, were compensated in part by a sort of public and psychological wage,” explaining why the White working-class united with the capitalist Whites to lay the structural foundation of modern White supremacist policies and practices, even though they were exploited by capitalism and had as similar economic experience as Black workers. We can view the margin of health gain that

White workers earn on Black workers' back because of occupational segregation in the healthcare institutions as the physical “wage of Whiteness.” The eradication of White supremacy and the dismantling of labor market mechanisms that uphold occupational segregation are widely supported philosophically by a large majority of healthcare institutions. (Alexis et al., 2020) Yet, the actual implementation of interventions designed to desegregate the healthcare workforce often progresses at a slow pace. (Association for American Medical Colleges, 2020) The physical “wage of Whiteness” enjoyed by workers at the top of the organizational hierarchy, especially those who believe this advantage will be taken away from them in the desegregated workplace, may be one of the critical resisting forces underlying the persistent occupational segregation in the healthcare institutions.

Third, we observed different levels of reduction in the hypertension inequity between the Black and White healthcare workforces across the four desegregation scenarios. Generally, we observed a greater reduction in hypertension when barriers to occupational class access are eliminated jointly for Black and female workers than when only racial barriers are eliminated. These findings reiterate the intersectionality of race and gender in the labor market process and their joint role in the social production of the workers’ health. Our study also reveals different degrees to which population health is improved depending on how desegregation is conducted. Taking the seats that should have belonged to Black and female workers back from White and male workers (scenario A and B) leads to narrowing the racial gap in hypertension, but with White and male workers facing a greater risk of hypertension. On the other hand, by making more seats available and prioritizing those seats for Black and female workers (scenario C and D), the racial gaps in hypertension will narrow due to a reduction in hypertension risks for both Black and White workforces. Workforce desegregation policies are known commonly as “diversity, equity, and inclusion (DEI) policies” and can target different stages of the labor market process. For example, a series of laws classified as affirmative action have been implemented to improve diversity in higher education (i.e., the key requirement for high-status healthcare occupations) and to ensure that racial distribution of workers employed by government contractors reflects the diverse community served by these organizations. (Arcidiacono, Lovenheim, & Zhu, 2015; Holzer, Harry; Neumark, 1999; Kurtulus, 2016) The American Association of Medical Colleges and other health professional organizations also established pipeline and mentoring programs to increase the physician workforce from historically underrepresented backgrounds. (Fontenot & McMurray, 2020; Jacob, 2015; Merchant & Omary, 2010) Because these DEI policies are carried out in concert with continuing efforts to eliminate the shortage of high-status healthcare workers (e.g., a partnership between healthcare and institutions to increase enrollment, federal legislatures to increase residency positions eligible for graduate medical education under Medicare, accelerated baccalaureate and master degree in nursing programs, the National Health Services Corp Student to Service Loan Repayment Program, etc.), DEI policies should not create adverse effects on the health of the overall healthcare workforce. Future studies should examine the health impact of specific DEI policies, as some DEI policies are more effective in desegregating the workforce than others. (Kalev et al., 2006)

The results presented in this chapter are an early iteration of our effort to improve knowledge of the role of work as a social determinant of health and health inequities. Our findings must be interpreted with several limitations in mind. First, the model we used to mimic how structural racism and sexism give rise to occupational segregation in the healthcare institutions and the pathogenesis of hypertension among healthcare workers simplified much more complex real-world processes. Other models that operationalize these processes differently or use different model assumptions may lead to a different conclusion. We encourage other researchers to modify our model structure or assess the impact of desegregation on hypertension inequity under the different model assumptions and further examine the sensitivity of our findings. Second, our prediction of hypertension status among workers considered the effect of job insecurity and psychosocial work environment, the two heavily researched occupational risk factors that are prevalent in the low-status occupational classes. Our study did not focus on the potential effect of work-related stressors reported in other previous studies to be prevalent among high-status workers, especially among non-White workers. Examples of such stressors include hiring and workplace discrimination, the experience of tokenism, John Henryism, and increased work-home life interference. (Bonham, Sellers, & Neighbors, 2004; Braboy Jackson et al., 1995; Grace & VanHeuvelen, 2019; Quillian, Pager, Hexel, & Midtbøen, 2017) Future studies should investigate the interplay between various stressors and examine the health impact of desegregation in light of possible concurrent exposure to these risks.

In conclusion, we highlight the role of occupational segregation as a driver of health inequities in Black and White workforces and provide the first evidence that desegregating the workforce will reduce racial health inequities and improve the overall population health. The policy window to dismantle structural racism and sexism in the labor markets – the key force underlying occupational segregation – is now. Policymakers can adapt the innovative microsimulation approach used in our study for future evaluation of health equity policies.

SUPPLEMENT 3.1

TABLE S3.1: Healthcare Occupational Classes and Their Proportional Representation in the White and Black Healthcare Workforces Based on the 2017 American Community Survey.

Class	2010 Standard Occupational Code	Occupation	White (N=6,864,442)	Black (N=1,719,595)
Health Diagnosing (Doctoral Degree)	29-1011	Chiropractors	12.5%	3.7%
	29-1020	Dentists		
	29-1041	Optometrists		
	29-1051	Pharmacists		
	29-1060	Physicians and Surgeons		
	29-1081	Podiatrists		
	29-1181	Audiologists		
	29-1131	Veterinarians		
Health Treating (Master's Degree)	29-1122	Occupational Therapists	43.0%	22.6%
	29-1123	Physical Therapists		
	29-1124	Radiation Therapists		
	29-1125	Recreational Therapists		

	29-1126	Respiratory Therapists		
	29-1031	Dieticians and Nutritionists		
	29-1071	Physician Assistants		
	29-1141	Registered Nurses*		
	29-1127	Speech Language Pathologists		
	29-112X; 29-1129	Other Therapists, Including Exercise Physiologists		
	29-1151; 29-1141	Nurse Anesthetists		
	29-11XX; 29-1141	Nurse Practitioners and Nurse Midwives		
	29-1199	Health Diagnosing and Treating Practitioners, All Other		
Health Technicians (Bachelor's Degree)	29-2010	Clinical Laboratory Technologists and Technicians	22.5%	24.2%
	29-2021	Dental Hygienists		
	29-2030	Diagnostic Related Technologists and Technicians		
	29-2041	Emergency Medical Technicians and Paramedics		

	29-2050; 29-2050	Health Practitioner Support Technologists and Technicians		
	29-2061	Licensed Practical and Licensed Vocational Nurses		
	29-2071	Medical Records and Health Information Technicians		
	29-2081	Opticians, Dispensing		
	29-2090	Miscellaneous Health Technologists and Technicians		
	29-9000	Other Healthcare Practitioners and Technical Occupations		
Healthcare Aides (Less than Bachelor's Degree)	31-1010	Nursing, Psychiatric, and Home Health Aides	21.9%	49.5%
	31-2010	Occupational Therapy Assistants and Aides		
	31-2020	Physical Therapist Assistants and Aides		
	31-9011	Massage Therapists		
	31-9091	Dental Assistants		
	31-9092; 31-909X	Medical Assistants		

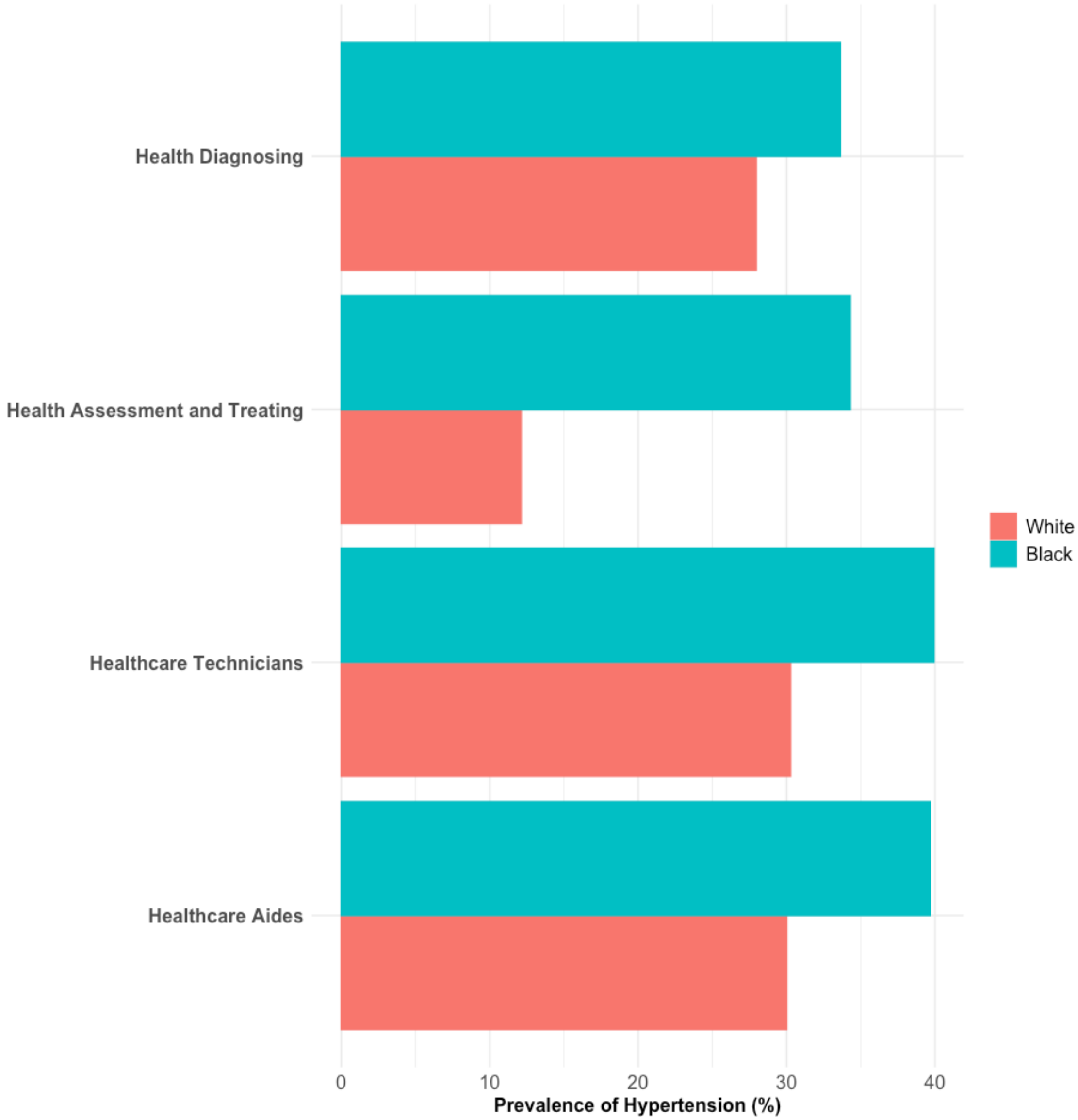
	31-9094; 31-909X	Medical Transcriptionists		
	31-9095; 31-909X	Pharmacy Aides		
	31-9096; 31-909X	Veterinary Assistants and Laboratory Animal Caretakers		
	31-9097; 31-909X	Phlebotomists		
	31-909X; 31-909X	Healthcare Support Workers, All Other, Including Medical Equipment Preparers		

Note: We grouped healthcare workers based on the educational requirement for their professional tasks and licensing. We put registered nurses (RN) in the "health treating" class, which requires a master's degree. In reality, RN is a broadly defined occupation; RN can hold an educational degree ranging from an associate to a doctoral level. Our decision to designate RN as a master-level "health treating" occupation was motivated by our need to differentiate RN, licensed practical nurses (LPN), and nursing aides into three separate occupational classes, reflecting different levels of work authority, occupational prestige, and average wage. This classification is consistent with the one used previously by Chou and Johnson (2008), although their classification focuses on job function rather than workers' position along the professional hierarchy.(Chou & Johnson, 2008)

SUPPLEMENT 3.2

FIGURE S3.1: Prevalence of Hypertension Among Healthcare Workers by Occupational Class and Race

We calculated the prevalence of hypertension among the US healthcare workforce using the 2014 to 2018 National Health Interview Survey data (NHIS). Sample individuals were asked, "During the past 12 months, have you had hypertension, also called high blood pressure"? The NHIS assigned sample individuals to the 1995 Occupational Code (OCC). For our analysis, we compare the 5-year prevalence of hypertension by race for individuals with the OCC 222 ("Health Diagnosing Occupations"), 223 ("Health Assessing and Treating Occupations), 301 (Health Technologist/Technician Occupations"), and 805 ("Health Service Occupations"). Note that the occupational classes based on the OCC are slightly different from those in Supplement S1 and may explain an inconsistent hypertension gradient by occupational class.


Health Diagnosing
Health Assessment and Treating
Healthcare Technicians
Healthcare Aides
0
10
20
30
40
Prevalence of Hypertension (%)
White
Black

SUPPLEMENT 3.3: Predicting Transition Probabilities to the Prehypertensive and Hypertensive States

At the start of our project, hypertension risk equations that incorporate work-related characteristics were not available. To our knowledge, this is still the case now. Thus, we estimated two equations to predict the probabilities of prehypertension and hypertension onset among workers using the data from the Coronary Artery Risk Development in Young Adults (CARDIA) study. Details about the study design and data collection protocols for the CARDIA study are available elsewhere.(Friedman et al., 1988) To derive these equations, we linked CARDIA participants' health and work characteristics collected as a part of the Year 15 follow-up assessment with the job title-based measures of the psychosocial work environment (PWE) that we derived from the job rating data from the Occupational Information Network (O*Net) database version 3.1.(O*NET Resource Center, 2019) We measured three dimensions of the PWE. The job demand measure includes ratings of workers 'ability to shift back and forth between activities/source of information, ability to concentrate on a task over a period of time without being distracted, the seriousness of the error, and the importance of being accurate in this job (score: 0-4; Cronbach's alpha=0.69).(Cifuentes et al., 2007) The job control measure includes ratings of whether the job makes use of workers' abilities, ability to try out their ideas, ability to make decisions on their own, and ability to plan their work with little supervision (score: 0-4; Cronbach's alpha=0.96).(Cifuentes et al., 2007) The support measure uses rating scales of whether workers on this job have supervisors who train their workers well and back them up with management (score: 0-2; Cronbach's alpha=0.78).(McCluney et al., 2018) These PWE measures were used in conjunction with participants' employment status. We assigned these PWE scores only to participants who worked full-time and part-time in Year 15. We assigned zero for all three measures to the unemployed participants.

We fitted the logistic regressions to estimate the probability of prehypertension and hypertension five years later (Year 20 follow-up assessment). We used a backward selection algorithm and selected the model with the lowest Bayesian Information Criteria (BIC) as the most parsimonious one. The Harrell c-statistic and the Hosmer-Lemeshow goodness-of-fit statistic were used to assess model discrimination and calibration, respectively. Below are the equations we used to predict the five-year probabilities of prehypertension (c-statistic=0.7; Hosmer-Lemeshow $\chi 2$=11.8) and hypertension (c-statistic=0.8; Hosmer-Lemeshow $\chi 2$=9.2) in our simulation.

$$Logit(5 - year\ hypertension) = -12.07 + 2.497 LogBMI + 0.775 Current\ Smoker + 1.710 Currently\ Prehypertensive + 0.656 Family\ History\ of\ Hypertension - 0.059 Work\ Full\ Time - 0.135 Work\ Part\ Time + 0.167 Job\ Demand - 0.347 Job\ Control - 0.160 Support + 0.024 Age + 0.197 Women \quad (1)$$

$$Logit(5 - year\ prehypertension) = -5.106 + 0.013 LogBMI - 0.424 Current\ Smoker + 1.155 Currently\ Prehypertensive + 0.509 Family\ History\ of\ Hypertension + 0.361 Work\ Full\ Time + 1.470 Work\ Part\ Time - 0.278 Job\ Demand - 0.657 Job\ Control - 0.206 Support - 0.078 Age + 0.004 Women \quad (2)$$

SUPPLEMENT 3.4: Tracking Hypertension Risk Factors and Hypertension Status Overtime

Our model tracked changes in exposure to hypertension risk factors in equations (1) and (2) in every cycle to determine hypertension status for the simulated workers. As the simulation progresses, the workers become one year older at the end of each cycle. Besides age, smoking status, physical activity, BMI, and employment status may change from one cycle to the next throughout the simulation period.

<u>Smoking Status and Physical Activity</u>

Workers may transition between the non-smoker, smoker, and quit state (Figure S3.2) and between the physically inactive and active state (Figure S3.3). We modeled these transitions with the state-transition model (STM). Both STMs used a one-year cycle. Transition probabilities for the smoking and physical activity STMs and their sources are shown in Table 3.1.

FIGURE S3.2: State Transition Diagram for Smoking Status

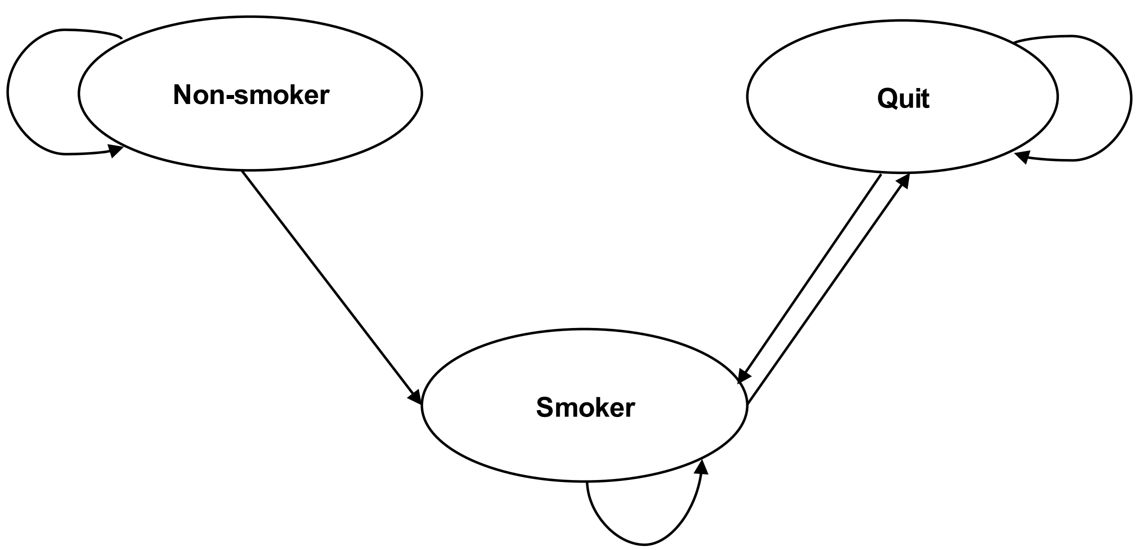
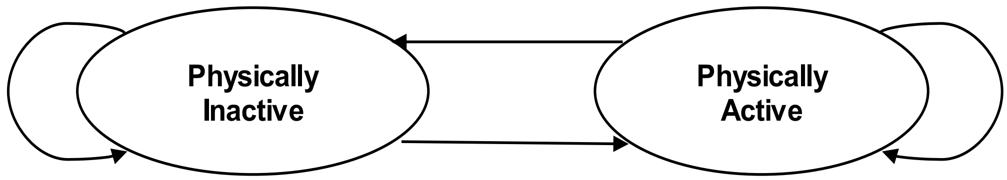


FIGURE S3.3: State Transition Diagram for Physical Activity



<u>Body Mass Index and Employment Status</u>

To track changes in BMI and employment status over time, we estimated autoregressive regression models to predict current BMI level and employment status conditioning on BMI level from two years ago and employment status one year ago, respectively.

The autoregressive linear regression model of the logarithm of BMI was estimated using the CARDIA data and is shown below.

$$LogBMI = 0.173 - 0.001Age - 0.036Physically\ Active - 0.007Current\ Smoker + 0.002Former\ Smoker + 0.978LogBMI\ Two\ Years\ Ago \quad (3)$$

The autoregressive multinomial regression models predicting whether healthcare workers in specific occupational class work full-time, part-time, or are unemployed were estimated using the American Community Survey (ACS) data (2012-2017).

Health Diagnosing Workers

$$\ln\left(Pr\ (full\ time)/Pr\ (unemployed)\right) = -15.561 - 0.024Age - 0.860Women - 0.466Black + 22.332Employed\ last\ year \quad (4)$$

$$\ln\left(Pr\ (part\ time)/Pr\ (unemployed)\right) = -51.658 + 0.009Age + 0.385Women - 1.065Black + 54.453Employed\ last\ year \quad (5)$$

Health Treating Workers

$$\ln\left(Pr\ (full\ time)/Pr\ (unemployed)\ \right) = -14.225 - 0.016Age - 0.110Women - 0.140Black + 19.519Employed\ last\ year \quad (6)$$

$$\ln\left(Pr\ (part\ time)/Pr\ (unemployed)\ \right) = -14.704 - 0.007Age + 1.015Women - 0.872Black + 17.333Employed\ last\ year \quad (7)$$

Healthcare Technicians

$$\ln\left(Pr\ (full\ time)/Pr\ (unemployed)\ \right) = -13.624 - 0.001Age - 0.071Women - 0.203Black + 17.474Employed\ last\ year \quad (8)$$

$$\ln\left(Pr\ (part\ time)/Pr\ (unemployed)\ \right) = -14.794 + 0.001Age + 1.042Women - 0.649Black + 16.357Employed\ last\ year \quad (9)$$

Healthcare Aides

$$\ln\left(Pr\ (full\ time)/Pr\ (unemployed)\ \right) = -13.624 - 0.001Age - 0.071Women - 0.203Black + 17.474Employed\ last\ year \quad (10)$$

$$\ln\left(Pr\ (part\ time)/Pr\ (unemployed)\ \right) = -14.794 + 0.001Age + 1.042Women - 0.649Black + 16.357Employed\ last\ year \quad (11)$$

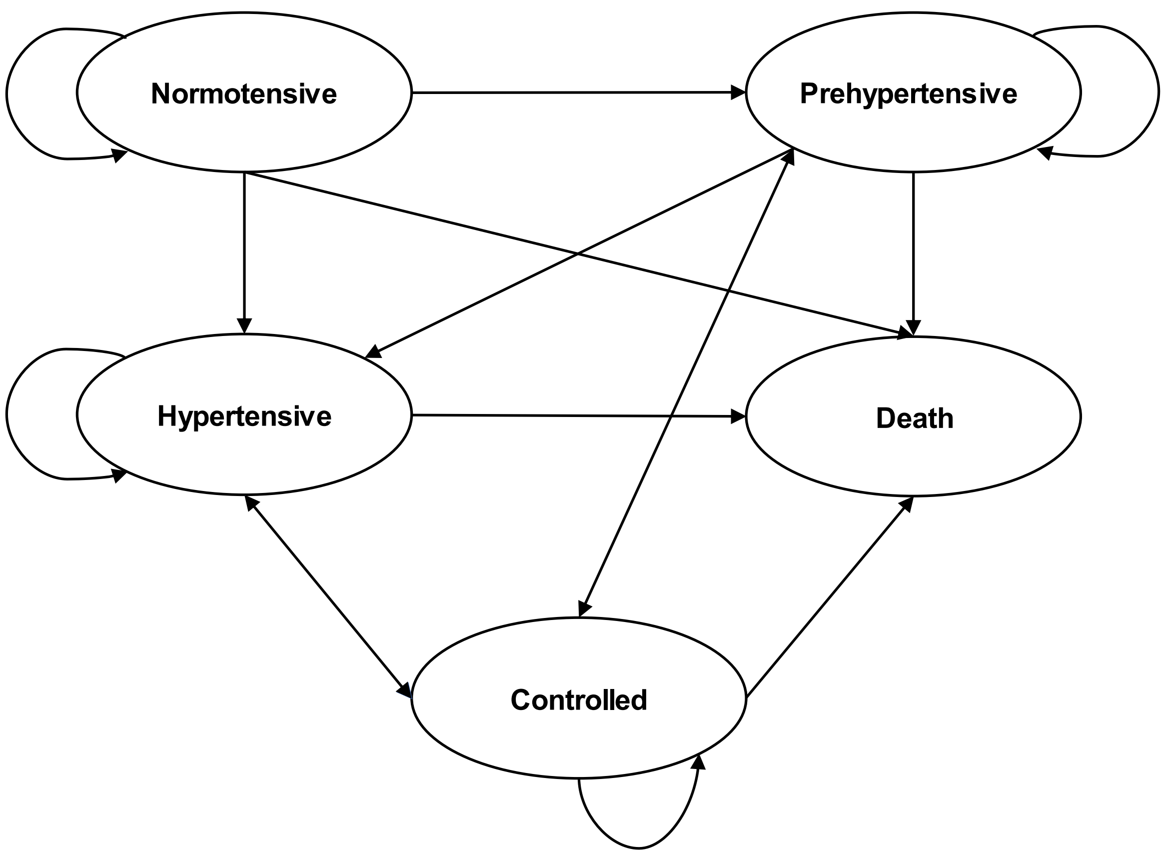
<u>Other Characteristics</u>

Workers' race, gender, occupational class, and family history of hypertension do not change over time. In all cycles, the baseline characteristics were used to estimate the relevant probabilities throughout the simulation. As mentioned above, the PWE scores are conditioned on the employment status. For example, suppose unemployed workers become employed either full-time or part-time. In that case, the model will "turn on" the PWE scores and use them to predict the probabilities of prehypertension and hypertension onset for that cycle.

Dynamic Transition Between States

Figure S3.4 is a state-transition diagram for hypertension used in our model. Over time, *normotensive* workers can remain normotensive, become prehypertensive, or become hypertensive. *Prehypertensive* workers can remain prehypertensive, become hypertensive, or become controlled. The probability for transitioning between the prehypertensive and controlled states was assumed to be the same as if workers receive behavioral modification advice (i.e., lose weight, reduce sodium intake, increase physical activity, use the Dietary Approaches to Stop Hypertension (DASH) diet) by their healthcare providers. Prehypertensive workers cannot return to the normotensive state. The probability for prehypertensive workers to become hypertensive is higher than for normotensive workers.(Egan & Stevens-Fabry, 2015) *Hypertensive* workers can remain hypertensive or become controlled. The latter transition was conditioning on the workers' access to hypertension medication and levels of adherence. Black hypertensive workers receive hypertension medications by healthcare providers at a higher probability than their White counterparts.(Samanic et al., 2020) Our model assumes that after hypertensive workers receive hypertension medications, they will remain on those medications as long as they remain hypertensive. For hypertensive workers who are not prescribed medications by their providers, we assumed that they have the same probability of receiving medication in the following cycle as when they first become hypertensive. Hypertensive workers may adhere to the medications at three levels: high (medication adherence rate (MPR)>0.80), medium (MPR of 0.50-0.79), and low (MPR<0.50). Each adherence level is associated with the probability of blood pressure control. Hypertensive workers who are not taking medications were assumed to have zero probability of becoming controlled. Workers with *controlled* blood pressure can remain controlled, become prehypertensive, or become hypertensive similar to normotensive workers. All workers may *die* during their careers from causes related to or unrelated to cardiovascular diseases (CVD). Compared to normotensive, prehypertensive, and controlled workers, hypertensive workers face a higher risk of CVD-related death but have the same risk of non-CVD death. Regardless of the health states, female workers face an additional risk of death from pregnancy-related causes.

FIGURE S3.4: State Transition Diagram for Hypertension



SUPPLEMENT 3.5

TABLE S3.2: Predicted Probabilities of Being in Each Occupational Class for 25-year-old Healthcare Workers Under the Status-quo and Four Counterfactual Scenarios

Scenario		**Health Diagnosing**	**Health Treating**	**Healthcare Technicians**	**Healthcare Aides**
Status Quo Scenario	White men	0.312	0.235	0.291	0.162
	Black men	0.109	0.151	0.33	0.409
	White women	0.055	0.409	0.252	0.283
	Black women	0.015	0.205	0.223	0.557
Scenario A [a]	White men	0.274	0.221	0.299	0.206
	Black men	0.274	0.221	0.299	0.206
	White women	0.046	0.363	0.246	0.346
	Black women	0.046	0.363	0.246	0.346
Scenario B [b]	White men	0.087	0.337	0.255	0.321
	Black men	0.087	0.337	0.255	0.321
	White women	0.087	0.337	0.255	0.321
	Black women	0.087	0.337	0.255	0.321
Scenario C [c]	White men	0.312	0.235	0.291	0.162
	Black men	0.312	0.235	0.291	0.162
	White women	0.055	0.409	0.252	0.283
	Black women	0.055	0.409	0.252	0.283
Scenario D [d]	White men	0.312	0.235	0.291	0.162
	Black men	0.312	0.235	0.291	0.162
	White women	0.312	0.235	0.291	0.162
	Black women	0.312	0.235	0.291	0.162

Note:

[a] Improved access to high-status occupational classes for Black workers, with improved access to low-status occupational classes for White workers; gender inequity still exists

[b] Improved access to high-status occupational classes for Black workers, with improved access to low-status occupational classes for White workers; gender inequity no longer exists

[c]Black men access occupational classes similarly to White men in the status-quo scenario, while Black women access occupational as White women

[d]All workers access occupational classes like White men in the status-quo scenario.

SUPPLEMENT 3.6

TABLE S3.3: Descriptive Statistics of Job Demand, Job Control, and Support Measures by Occupational Class.

We created the empirical distribution of job demand, job control, and support for all classes of healthcare workers. We linked the SOC-based PWE scores described earlier to the representative sample of healthcare workers sampled to participate in the ACS (2012-2017). Below are the descriptive statistics of the PWE scores from our empirical distributions. In our simulation model, we randomly drew the PWE scores for each simulated worker from the distributions specific to their occupational class.

Occupational Class	PWE Dimension	Mean	SD	Min	Q1	Q2	Q3	Max
Health Diagnosing	Job Demand	2.25	0.17	1.54	2.22	2.32	2.32	2.57
	Job Control	3.47	0.23	3.00	3.55	3.57	3.57	3.72
	Support	0.78	0.10	0.60	0.79	0.79	0.79	1.02
Health Treating	Job Demand	2.13	0.25	1.46	2.18	2.18	2.18	3.13
	Job Control	2.71	0.21	2.20	2.62	2.62	2.62	3.30
	Support	1.03	0.02	1.00	1.02	1.02	1.02	1.17
Healthcare Technicians	Job Demand	2.12	0.16	1.82	2.08	2.12	2.12	2.40
	Job Control	2.28	0.28	1.99	2.15	2.15	2.39	3.02
	Support	1.14	0.09	0.90	1.07	1.12	1.20	1.26
Healthcare Aides	Job Demand	1.85	0.28	1.47	1.67	1.67	2.07	2.45
	Job Control	1.63	0.09	1.57	1.58	1.58	1.70	1.97
	Support	1.22	0.05	1.15	1.19	1.19	1.25	1.35

SUPPLEMENT 3.7

TABLE S3.4: Mean Prevalence (Cases per 100) of Hypertension Among Black and White Healthcare Workforces by Age Group Under the Status Quo and Four Counterfactual Scenarios

Age	Status-quo		Scenario A [a]		Scenario B [b]		Scenario C [c]		Scenario D [d]	
Group	White	Black	White	Black	White	Black	White	Black	White	Black
25-29	4.0	4.9	4.0	4.7	4.0	4.7	4.0	4.7	3.8	4.5
30-34	6.2	7.6	6.3	7.2	6.3	7.2	6.2	7.1	5.8	6.7
35-39	9.0	11.0	9.1	10.5	9.1	10.4	9.0	10.3	8.5	9.8
40-44	12.3	14.7	12.4	14.1	12.4	14.0	12.3	13.9	11.7	13.3
45-49	15.6	18.3	15.9	17.7	15.9	17.6	15.7	17.5	15.1	16.8
50-54	19.1	21.7	19.3	21.1	19.3	21.1	19.2	20.9	18.5	20.2
55-59	22.5	24.8	22.6	24.1	22.6	24.1	22.5	24.0	21.8	23.4
60-64	25.6	27.5	25.7	26.9	25.7	26.9	25.6	26.8	24.9	26.2
25-64	14.3	16.3	14.4	15.8	14.4	15.8	14.3	15.6	13.8	15.1

Note:

[a] Improved access to high-status occupations for Black workers, with improved access to low-status occupations for White workers; gender difference still exists

[b] Improved access to high-status occupations for Black workers, with improved access to low-status occupations for White workers; gender difference no longer exists

[c] Black men access occupations similarly to White men, while Black women access occupations as White women

[d] All workers access occupations similarly to White men.

CHAPTER 4

FROM A COHORT TO A POPULATION MODEL

4.1 MOTIVATION

Microsimulations are effective policy evaluation tools if they are able to predict trends correctly. In other words, results produced during the status-quo simulation must be consistent (on average) with the empirical data. Models lacking this capacity may predict questionable impacts of proposed policies and should not be used for policy evaluation. (Committee of the Assessment of Agent-Based Models to Inform Tobacco Product Regulation, Board on Population Health and Public Health Practice, & Institute of Medicine, 2015)

We discussed in the previous chapter our use of a microsimulation to predict the reduction in hypertension inequity between the Black and White healthcare workforces under several desegregation scenarios/strategies. While such predictions inform us about the direction of these changes (e.g., decrease in the hypertension prevalence gap), we cannot say with certainty that the extent of the changes we observed is what these desegregation strategies will produce in the real-world setting. Before doing so, we must validate the results from our status-quo simulation against the empirical data. Suppose the status-quo prediction from our model is consistent with what we currently observed among healthcare workforces in the US. Then, we can be more confident that our simulation model effectively replicates employment and hypertension dynamics. Therefore, the changes our model predicted in the counterfactual simulation are likely the "true" size of the impacts.

Our current microsimulation is a cohort model that tracks employment dynamics and hypertension trajectories among a fixed set of simulated workers overtime. While the simulated workers may die and “leave” the cohort prematurely, no new workers can enter this cohort. This setup is consistent with typical longitudinal observational studies (e.g., CARDIA). Nevertheless, the problem we encounter when searching for empirical data to validate our status-quo simulation results is that, to our knowledge, there are no longitudinal studies that follow employment and hypertension trajectories among all four classes of healthcare workers. One study that comes close to our needs is the Nurses’ Health Study (NHS) that follow female nurses (aged 30 to 55 years at baseline for the original NHS cohort, 25 to 42 years for NHS II, and 19-46 years for NHS III) and track changes in their socioeconomic and health statuses. (Bao et al., 2016) Besides the fact that the NHS only includes one class of healthcare workers, the data study data is not easily accessible made this data source not feasible for our model validation.

Given the lack of cohort data for model validation, we turned our attention to another possible type of data: surveillance data. Whereas cohort studies follow a set of participants from baseline to the end of the study and estimations of disease prevalence are based on the number of uncensored participants at various time points, surveillance studies have a “new” cohort (i.e., the population at time *t*) whenever the disease prevalence is estimated. The new cohort (e.g., *t+1*) may consist of participants from time *t,* those who become eligible to participate in time *t+1,* and those who were eligible in time *t* but did not participate earlier. Estimates from these surveillances are calculated based on the total population at a particular point in time. Hence, the denominators for those estimates change every time to reflect the current makeup of the population of interest at specific time points.(Nsubuga et al., 2006)

Several governmental agencies conduct employment and hypertension surveillance. Two potential sources of estimates of unemployment rates and hypertension prevalence among all classes of healthcare workers are the American Community Survey (ACS) (US Census Bureau, 2021) and the National Health Interview Survey (NHIS)(Center for Disease Control and Prevention, 2021), respectively. Both the ACS and NHIS sample US resident annually and ask them to report their occupations. It is important to note that the ACS and NHIS are not explicitly designed for healthcare workers; rather, sizable healthcare workers participated in these data collections. When data from multiple years are combined, the regional (Northeast, Midwest, South, Western US) weighted unemployment rates and hypertension prevalence can be estimated to use for our validation.

To facilitate using these data for validation, we must change our model setup from a cohort- to a population-based microsimulation model. To do so requires an overhaul of our model specifications that is beyond the scope of this dissertation. While we cannot complete the whole process, we took some key initial steps, including conceptualizing how we will track the employment status of simulated workers and calibrating necessary parameters for this simulation process. Following Robert Axelrod's K.I.S.S. (Keep It Simple, Stupid) principle, we focused only on healthcare aides (i.e., one occupational class only rather than all four at once) who search for jobs in the Chicago-Naperville-Elgin, IL-IN-WI metropolitan statistical area (refer to as "the Chicago area" henceforth) for this project.

4.2 METHOD

4.2.1 Population Simulation

We simulated one-tenth the size of the healthcare aides workforce in the Chicago area in 2018 according to the estimated number from the ACS (n=12,454) to initialize our simulation (*t*=0). We characterized each worker by race (Black, White, other races), gender (male, female), age (range from 25-64) so that the overall population closely resembled the target population. In addition to their sociodemographic characteristics, we also characterized each worker's employment status (employed or unemployed), work experience, and their current hourly wage for employed workers.

In our model, work experience is tied somewhat to age. We assume that all workers in our model start working at age 25 and will accrue work experience whenever they are employed. For example, the maximum possible experience for 35-year-old workers who have never lost a job throughout their career is ten years. On the other end, 35-year-old workers who have never been employed will have zero years of work experience. Supposed that throughout a 10-year career, 35-year-old workers are unemployed for one year, the total work experience on their resume will be nine years. For the first batch of workers (*t*=0), we assigned workers' work experience randomly by sampling it from a possible range given their age at that time (uniform distribution). For 35-year-old workers, for example, the possible range from which to sample is between zero and ten years.

Workers' hourly wage is based on the specific job that they hold. We generated a list of job openings for healthcare aides in Chicago in 2018, assuming that the total number of jobs in this market remains the same over time. The number of jobs was calculated by multiplying the estimated number of workers by the estimated employment rate. At *t*=0, the employment rate for this workforce was estimated to be 94.4%; hence, in our model, there are 0.944 x 12,454 ≈ 11,757 jobs. Each job is associated with an hourly log wage, to which we assigned based on the empirical distribution from the Labor Statistics' Occupational Employment and Wage Statistics.(US Bureau of Labor Statistics, 2021).

Our model assumes that all workers will retire and leave the workforce at age 65 years. To make sure that the size of the workforce in our model is somewhat static over time, our model sampling the number of new entries to add to the current labor force from the Poisson distribution that is parameterized by lambda equal to the number of 64-year-old workers who will retire in the following cycle. These 24-year-old workers compete for jobs with workers aged 63 years and younger already in the labor force; they will enter the labor market when they become 25 years old. We characterized the new entries the same way we did for those currently in the labor force. In this version of our model, all workers remain alive during their 40-year careers.

4.2.2 Job Application-Matching Process

As mentioned above, workers aged 24 (new entries, soon to be in the labor force) to 63 (referred to as "eligible workers" henceforth) competing for jobs in the labor market. We chose to simulate a job application-matching process rather than predicting workers' employment status using a regression model like in the previous chapter to reflect the fact that the job process is a demand-supply process.

At the beginning of every cycle, eligible workers survey all the jobs in the labor market and apply to ten of them with an offered wage in the same or higher decile than their current wage. The benchmark currently employed workers use to decide on which job to apply for is their current wage. For unemployed workers and new entries, the benchmark is $0. All workers have what we call a "candidacy score," a simple rubric used by employers for ranking workers and deciding which workers to whom they will offer the jobs. Our version of the candidacy score factors workers' race, gender, work experience, and a history of unemployment to reflect the current literature on factors associated with employment discrimination. This simplified rubric gives a "premium" to workers with higher work experience and White workers. Our simplified rubric also includes a penalty for Black workers and unemployed workers when they applied for the jobs. It is important to recognize that many other factors likely explain employers' preferences of certain workers over others in the real world. We wanted to start with a simplified rubric, ensuring that it can generate the expected trend and continue to add more parts to it in the future.

$$Score=\beta_0 + \beta_1 Work\ experience - \beta_2 Currently\ Unemployed + \beta_3 White - \beta_4 Black$$

For each job, the employers made their first offer to the applicants with the highest candidacy score. If more than one applicant has the highest score, the offer is made randomly to one of these applicants. Given this rule, three scenarios are possible during the initial round of offer:

1. Applicants receive more than one offer. In this case, the workers will select the job with an hourly wage in the highest decile. If more than one offer fits this criterion, the workers will randomly accept one of these job offers.
2. Applicants receive only one offer. In this case, the workers will accept their one job offer.

3. Applicants receive no offer. In this case, workers will join the employers' "backup" pool.

In the second to fifth rounds of job matching, the workers who do not receive an offer in the previous rounds are reconsidered using the same process. The eligible pool for the later rounds is relatively smaller than the previous rounds as workers with job offers leave the job matching process. Any unfilled jobs after the end of the fifth round will be offered to and automatically accepted by the incumbents if they have not received any offered at that point. If the incumbents have other job offers in hand, those jobs will remain unfilled in the next cycle. At the end of each job application-matching process, our model tallies the total number of workers in the labor force in the following cycle (cycle t+1) and the proportion of unemployed workers by race.

We allowed our model to run for 40 cycles; each cycle represents one year. We picked a cycle length of one year to coincide with a typical annual review process. While not all workers in the real world search for new jobs every year, they receive their performance evaluations annually. The results of such a process can be 1) workers get promoted (i.e., get a higher wage), 2) workers keep their current job with no promotion, or 3) workers lose their jobs. While using a one-year cycle makes sense in this instance, our use of this cycle length also forces us to automatically assume that unemployed workers will remain employed for one whole year.

4.2.3 Calibrating the candidacy score parameters

Calibration is the process by which values of key model unknowns are determined so that the outcomes of the simulation process fit with specific targets. To ensure that unemployment rates generated by our model closely match the race-specific rates observed among workers in the Chicago area, we calibrated parameters β_0 to β_5 in the candidacy score using a random sampling method. (Vanni et al., 2011) We create 100 parameter sets with the Latin hypercube sampling technique. (Blower & Dowlatabadi, 1994) The possible values for all parameters, except $\beta_1$for work experience, were between zero to ten. For β_1, we set the possible range to be between zero to one because work experience can potentially increase in every cycle, unlike other characteristics in the candidacy score equation. Doing so prevent work experience to be the only key deciding factors for hiring, a scenario that does not reflect the conditions seen in the current labor market. For this project, we have three targets to match: 1) unemployment rate among White workers, 2) unemployment rate among Black workers, and 3) unemployment rate among workers from other racial backgrounds. We allowed the job application-matching process to occur for 40 cycles for each set of parameters. We then calculated the race-specific and overall log-likelihood comparing unemployment rates that the model simulated for the last ten cycles to the observed rates from the ACS. The parameter set that produced a model output with the lowest overall log-likelihood was considered best fitted.

4.3 RESULTS

Among the 100 parameter sets we tested for our candidacy score equation, our calibration algorithm identified the one below as the set that produced unemployment rates closest to the three target rates.

Score=1.77 + 0.88Work experience – 9.47Currently Unemployed + 4.74White – 3.39Black

Table 4.1 displays the estimated size of the healthcare aide labor force in the Chicago area (all races, not just Black and White workers), the estimated number of jobs available, and comparisons of the unemployment rates for the Black and the White workforces estimated from the ACS 2018 to the rates from our best-fitted model.

TABLE 4.1: Calibration Model Parameters and Outputs

	ACS 2018	**Microsimulation**[b]
Estimated size of the labor force (25-64 years)	124,540	12,454
Estimated available jobs[a]	117,685	11,769
Unemployment rate (%) – White workforce	3.6	4.3
Male	6.2	3.9
Female	3.2	4.3
Unemployment rate (%) – Black workforce	9.3	11.7
Male	0.0	10.5
Female	9.9	11.8

Notes:

a. Estimated available jobs are from total employment rates of 94.5% times the estimated size of the labor force
b. Predicted unemployment rate are based on the mean predicted rate from the last ten simulation cycles

Figure 4.1 shows the simulated unemployment rates using the best parameter set for the candidacy score compared with the ACS rates. The race-specific unemployment rates from our model were consistently higher than the estimated rates from the ACS rates. The mean unemployment rates from cycles 30 to 40 of the simulation are 4.3% for the White workforce (3.6% from the ACS) and 11.7% for the Black workforce (9.3% from the ACS). The simulated race-gender rates were less consistent with the ACS rates (Figure 4.2). One important thing to note here is that the race-gender estimates with the ACS data were based on a small number of sampled individuals. For example, the unemployment rate for Black male workers is zero, suggesting that the race-gender rates we estimated from the ACS data may not be the good targets to which we should compare our result to start.

FIGURE 4.1: Comparison Between Race-specific Unemployment Rates from the Microsimulation Model Using the Best Fitted Parameter Set for the Candidacy Score and the Estimated Rates from the American Community Survey 2018 (Dash Lines)

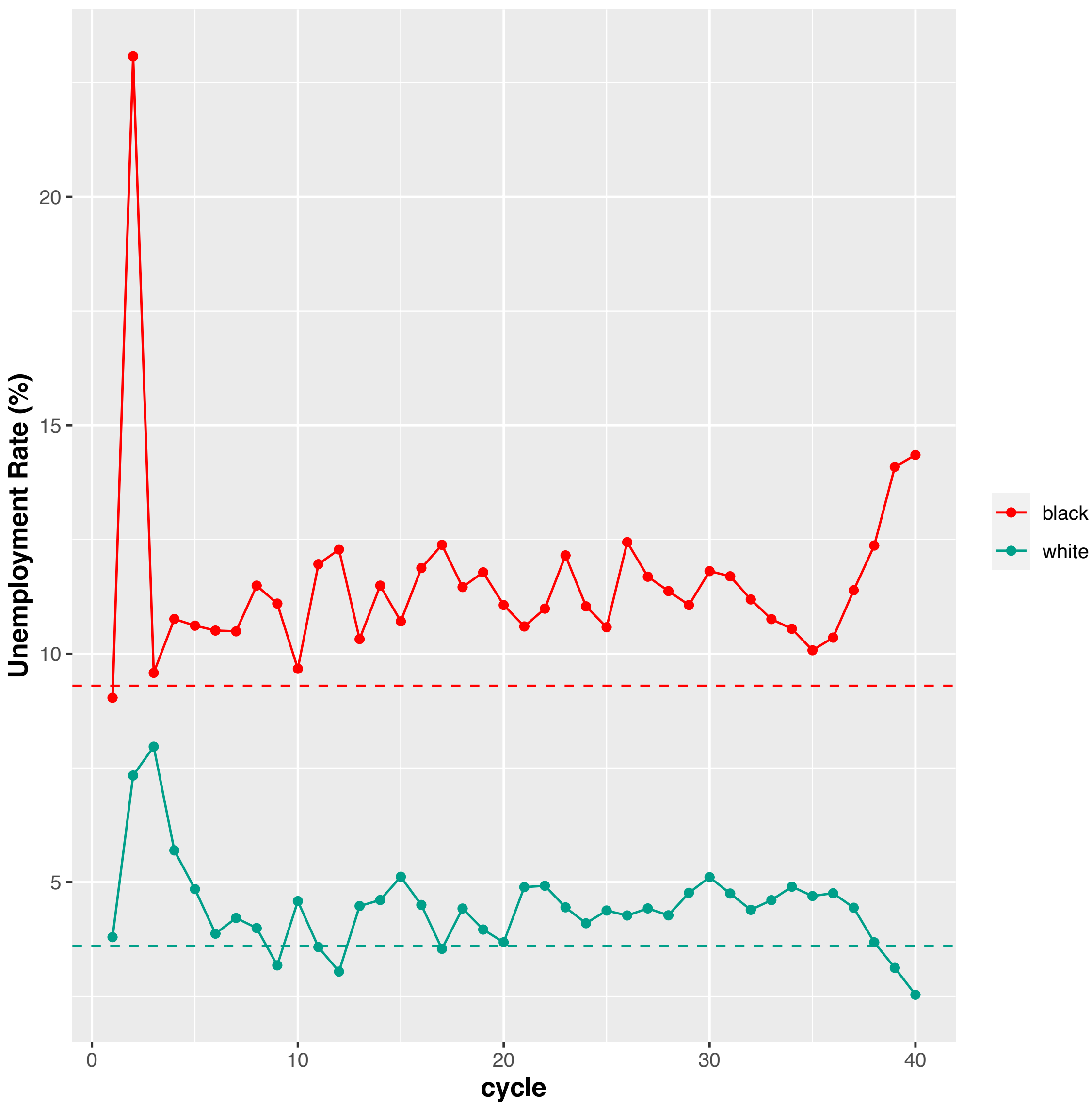
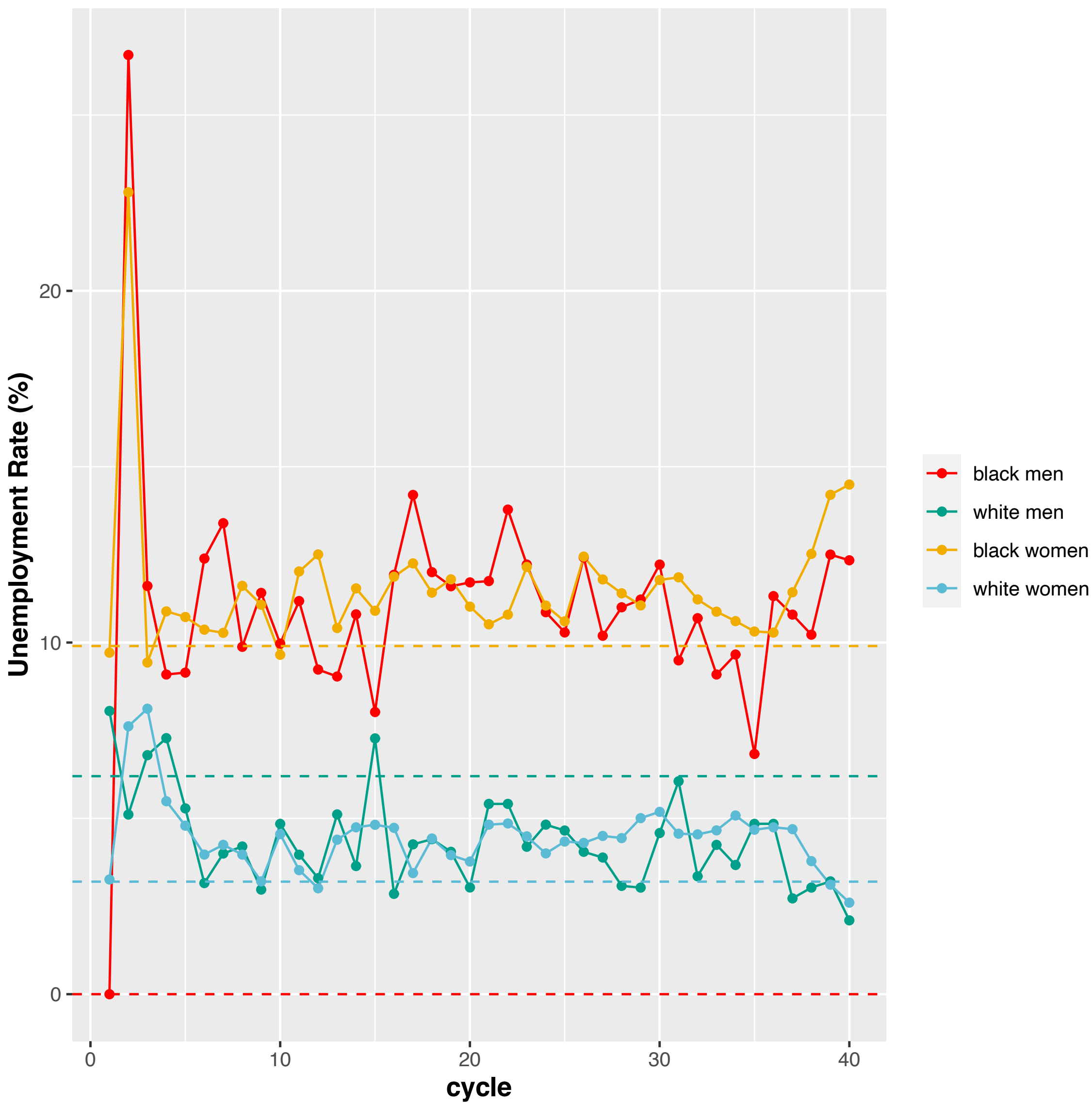


FIGURE 4.2 Comparison Between Race-gender-specific Unemployment Rates from the Microsimulation Model Using the Best Fitted Parameter Set for the Candidacy Score and the Estimated Rates from the American Community Survey 2018 (Dash Lines)



4.4 REFLECTIONS AND NEXT STEPS

Our calibration process did not identify a parameter set for the candidacy score that closely matches the trends among healthcare aides suggested by the ACS data. The simulated unemployment rates among the Black workforce were higher while those of the White workforce were lower than the rates from the ACS. There are many possible explanations for these deviations.

First, we did not use a large enough number of parameter sets in our calibration. Because the random search method must find the "right" parameter set from a limited universe of randomly generated parameter sets, giving the algorithm a larger universe to search from may increase the possibility of finding the right one. Future efforts, however, should utilize targeted search strategies. A larger number of samples should be used; however, possible ranges for each parameter should be confined based on results from the previous run. Furthermore, given the number of parameters in our candidacy score, other calibration techniques will be considered in our next step. Two potential calibration methods are the downhill simplex method and the simulated annealing method. The downhill simplex method, commonly referred to as the Nelder-Mead method, searches for optimized parameter sets from a simplex of N+1 dimensions (seven-dimension simplex in our case). The shape of the simplex changes from one iteration to the next to avoid combinations that would not have produced maximal goodness-of-fit statistics. The simulated annealing method introduces an artificial parameter called "temperature" that controls where the algorithm searches for the optimal parameter set. (Vanni et al., 2011)

Second, the job application-matching process used in our model may have "wreaked havoc." We programmed our model to make all workers compete for a job in every cycle. Employers reevaluate who to hire at the beginning of each cycle and offer the job to workers with the highest candidacy score. What we did not expect is that this process can make currently employed workers who are not "competitive" in the job market lose their current jobs if other employers do not select them for any jobs to which they applied, and their current jobs have already been offered to other workers with a higher candidacy score. We found this out because when we let our model conducted job matching for one instead of five rounds, the simulated unemployment rates were unexpectedly high. Increasing the number of rounds in the job matching process in our model helps to a certain level. There are more chances for employers who do not find the "right" worker and the workers who do not get selected in the initial rounds to find each other. With the right number of rounds, we may be able to simulate unemployment rates that are more consistent with the empirical rates.

Third, we simplified the job application-matching process occurring in the real world too much. For the current iteration, we intentionally design the job application-matching simulation to be very simple yet consistent with previous studies of this kind (Gemkow, Neugart, Gemkow, & Neugart, 2011; Neugart, 2004; Smith & Zenou, 2003; Tassier & Menczer, 2008; Wozniak, 2016) and the literature on labor market discrimination. (Browne & Misra, 2003; Pager, Bonikowski, & Western, 2009; Pedulla & Pager, 2019; Quillian et al., 2017; Wingfield & Chavez, 2020) Our model requires several assumptions. Key assumptions that are arguably strict/unrealistic are 1) workers do not die between age 25 to 64 years, and 2) workers do not leave the labor force at all during their careers. In the future iterations of our model, we will relax the first assumption to allow workers to die prematurely, either because of hypertension-related causes or other causes. As for the second assumption, one way to relax it is by incorporating the probability of getting pregnant and leaving the labor market temporarily to care for their newborns for female workers. The healthcare workforce, particularly those working in low-status occupations, consists largely of female workers. Allowing workers in the simulation models to not search for jobs temporarily may make the model more realistic.

Lastly, it is possible that our model could not create the estimated unemployment trends because the estimates from the ACS were inaccurate. The rates we used as targets for our calibration were calculated from a small number of healthcare aides randomly living in the Chicago area and were selected to participate in the ACS in 2018. Despite applying an appropriate weight scheme, estimates based on a very small sample can be unreliable. We see an example of this problem in the estimated unemployment rate for White male healthcare aides discussed earlier. Combining the data from multiple years to create a larger sample size may allow us to estimate unemployment rates more accurately. In our future research, we will also investigate if other data (e.g., Survey of Income and Program Participation) may be a better source of estimation.

BIBLIOGRAPHY

Acevedo, P., Mora-Urda, A. I., & Montero, P. (2019). Social Inequalities in Health: Duration of Unemployment Unevenly Effects on the Health of Men and Women. *The European Journal of Public Health*, *30*(2), 305–310. https://doi.org/10.1093/eurpub/ckz180

Ahonen, E. Q., Fujishiro, K., Cunningham, T., & Flynn, M. (2018). Work as an Inclusive Part of Population Health Inequities Research and Prevention. *Am J Public Health*, *108*, 306–311. https://doi.org/10.2105/AJPH

Alexis, D. A., Kearney, M. D., Williams, J. C., Xu, C., Higginbotham, E. J., & Aysola, J. (2020). Assessment of Perceptions of Professionalism Among Faculty, Trainees, Staff, and Students in a Large University-Based Health System. *JAMA Network Open*, *3*(11), e2021452. https://doi.org/10.1001/jamanetworkopen.2020.21452

Arcidiacono, P., Lovenheim, M., & Zhu, M. (2015). Affirmative Action in Undergraduate Education. *Annual Reviews of Economics*, *7*(1), 487–518.

Association for American Medical Colleges. (2020). *The Complexities of Physician Supply and Demand: Projections from 2013 to 2025 Final Report*. Washington, DC.

Aust, B., Rugulies, R., Skakon, J., Scherzer, T., & Jensen, C. (2007). Psychosocial Work Environment of Hospital Workers: Validation of a Comprehensive Assessment Scale. *International Journal of Nursing Studies*, *44*, 814–825. https://doi.org/10.1016/j.ijnurstu.2006.01.008

Bailey, Z. D., Krieger, N., Agénor, M., Graves, J., Linos, N., & Bassett, M. T. (2017). Structural Racism and Health Inequities in the USA: Evidence and Interventions. *Lancet*, *389*, 1453–1463. https://doi.org/10.1016/S0140-6736(17)30569-X

Beck, R. J., Pauker, S. G., Gottlieb, J. E., Klein, K., & Kassirer, J. P. (1982). A Convenient Approximation of Life Expectancy (The "DEALE") II. Use in Medical Decision-Making. *The American Journal of Medicine*, *73*(889–897).

Benach, J., Vives, A., Amable, M., Vanroelen, C., Tarafa, G., & Muntaner, C. (2014). Precarious Employment: Understanding an Emerging Social Determinant of Health. *Annu. Rev. Public Health*, *35*, 229–253. https://doi.org/10.1146/annurev-publhealth-032013-182500

Benjamin, E. J., Salim Virani, C. S., Chair Clifton Callaway, C.-V. W., Chamberlain, A.

M., Alexander Chang, M. R., Susan Cheng, M., … Paul Muntner, F. (2018a). Heart Disease and Stroke Statistics-2018 Update A Report From the American Heart Association. *Circulation*, *137*, 67–492. https://doi.org/10.1161/CIR.0000000000000558

Benjamin, E. J., Salim Virani, C. S., Chair Clifton Callaway, C.-V. W., Chamberlain, A. M., Alexander Chang, M. R., Susan Cheng, M., … Paul Muntner, F. (2018b). Heart Disease and Stroke Statistics-2018 Update A Report From the American Heart Association. *Circulation*, *137*, 67–492. https://doi.org/10.1161/CIR.0000000000000558

Blower, S. M., & Dowlatabadi, H. (1994). Sensitivity and Uncertainty Analysis of Complex Models of Disease Transmission: An HIV Model, as an Example. *International Statistical Review / Revue Internationale de Statistique*, *62*(2), 229. https://doi.org/10.2307/1403510

Bonham, V., Sellers, S. L., & Neighbors, H. W. (2004). John Henryism and Self-Reported Physical Health Among High–Socioeconomic Status African American Men. *American Journal of Public Health*, *94*(5), 737–738. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1448327/pdf/0940737.pdf

Bonilla-Silva, E. (2004). "New Racism," Color-Blind Racism, and the Future of Whiteness in America. In *White Out* (1st ed., pp. 268–281). Routledge. https://doi.org/10.4324/9780203412107-29

Braboy Jackson, P., Thoits, P. A., & Taylor, H. F. (1995). Composition of the Workplace and Psychological Well-Being: The Effects of Tokenism on America's Black Elites. *Social Forces*, *74*(2), 543–557. Retrieved from https://www-jstor-org.ezp3.lib.umn.edu/stable/pdf/2580491.pdf?refreqid=excelsior%3Ab0fa0131c642f3d01322fcca6ecfb747

Browne, I., & Misra, J. (2003). The Intersection of Gender and Race in the Labor Market. *Annu. Rev. Sociol*, *29*, 487–513. https://doi.org/10.1146/annurev.soc.29.010202.100016

Budig, M. J., Hodges, M. J., & England, P. (2019). Wages of Nurturant and Reproductive Care Workers: Individual and Job Characteristics, Occupational Closure, and Wage-

Equalizing Institutions. *Social Problems*, *66*, 294–319. https://doi.org/10.1093/socpro/spy007

Bureau of Labor Statistics. (2012). *The Recession of 2007–2009*. Washington, DC. Retrieved from http://www.bls.gov/cps/cps_htgm.htm.

Bureau of Labor Statistics. (2020). Table A-13. Employed and Unemployed Persons by Occupation, Not Seasonally Adjusted. Retrieved August 13, 2019, from https://www.bls.gov/webapps/legacy/cpsatab13.htm

Burgard, S. A., Brand, J. E., & House, J. S. (2009). Perceived Job Insecurity and Worker Health in the United States. *Social Science and Medicine*, *69*(5), 777–785. https://doi.org/10.1016/j.socscimed.2009.06.029

Burgard, S. A., & Kalousova, L. (2015). Effects of the Great Recession: Health and Well-Being. *Annu. Rev. Sociol*, *41*, 181–201. https://doi.org/10.1146/annurev-soc-073014-112204

Cantor, M. N., & Thorpe, L. (2018). Integrating Data on Social Determinants of Health into Electronic Health Records. *Health Affairs*, *37*(4), 585–590. https://doi.org/10.1377/hlthaff.2017.1252

Chen, M., Tan, X., & Padman, R. (2020). Social Determinants of Health in Electronic Health Records and Their Impact on Analysis and Risk Prediction: A Systematic Review. *Journal of the American Medical Informatics Association : JAMIA*, *27*(11), 1764–1773. https://doi.org/10.1093/jamia/ocaa143

Chen, Y.-H., Glymour, M., Riley, A., Balmes, J., Duchowny, K., Harrison, R., … Bibbins-Domingo, K. (2021). Excess Mortality Associated with the COVID-19 Pandemic Among Californians 18–65 years of age, by Occupational Sector and Occupation: March through November 2020. *PLOS ONE*, *16*(6), e0252454. https://doi.org/10.1371/JOURNAL.PONE.0252454

Chobanian, A. V., Bakris, G. L., Black, H. R., Cushman, W. C., Green, L. A., Izzo, J. L., … Committee, the N. H. B. P. E. P. C. (2003). Seventh Report of the Joint National Committee on Prevention, Detection, Evaluation, and Treatment of High Blood Pressure. *Hypertension*, *42*(6), 1206–1252. https://doi.org/10.1161/01.HYP.0000107251.49515.c2

Chou, C.-F., & Johnson, P. J. (2008). Health Disparities among America's Health Care Providers: Evidence from the Integrated Health Interview Series, 1982 to 2004. *Journal of Occupational and Environmental Medicine*, *50*(6), 696–704. https://doi.org/10.1097/JOM.0b013e31816515b5

Chung-Bridges, K., Muntaner, C., Fleming, L. E., Lee, D. J., Arheart, K. L., Leblanc, W. G., … Davila, E. P. (2008). Occupational Segregation as a Determinant of US Worker Health. *American Journal of Industrial Medicine*, *51*, 555–567. https://doi.org/10.1002/ajim.20599

Cifuentes, M., Boyer, J., Gore, R., D'Errico, A., Tessler, J., Scollin, P., … Team, P. in H. R. (2007). Inter-method Agreement between O*NET and Survey Measures of Psychosocial Exposure among Healthcare Industry Employees. *American Journal of Industrial Medicine*, *50*(7), 545–553. https://doi.org/10.1002/ajim.20480

Clougherty, J. E., Eisen, E. A., Slade, M. D., Kawachi, I., & Cullen, M. R. (2011). Gender and Sex Differences in Job Status and Hypertension. *Occupational and Environmental Medicine*, *68*(1), 16–23. https://doi.org/10.1136/oem.2009.049908

Compton, W. M., Gfroerer, J., Conway, K. P., & Finger, M. S. (2014). Unemployment and Substance Outcomes in the United States 2002–2010. *Drug and Alcohol Dependence*, *142*, 350–353. https://doi.org/10.1016/j.drugalcdep.2014.06.012

Cook, N. R. (2007). Use and Misuse of the Receiver Operating Characteristic Curve in Risk Prediction. *Circulation*, *115*(7), 928–935. https://doi.org/10.1161/CIRCULATIONAHA.106.672402

Daniel, H., Bornstein, S., & Kane, G. (2018). Addressing Social Determinants to Improve Patient Care and Promote Health Equity: An American College of Physicians Position Paper. *Annals of Internal Medicine*, *168*(577–578). https://doi.org/10.2105/AJPH

Du Bois, W. (1998). *Black Reconstruction in America, 1860-1880* (1997th ed.). Free Press.

Duffy, M. (2011). *Making Care Count: A Century of Gender, Race and Paid Care*. Rutgers University Press.

Egan, B. M., & Stevens-Fabry, S. (2015). Prehypertension — Prevalence, Health Risks, and Management Strategies. *Nature Reviews Cardiology*, *12*(5), 289–300. https://doi.org/10.1038/nrcardio.2015.17

Ferrie, J. E., Shipley, M. J., Gideon, M., Stansfeld, S. A., & Smith, G. D. (1998). An Uncertain Future: The Health Effects of Threats to Employment Security in White-Collar Men and Women. *American Journal of Public Health*, *88*(7), 1030–1036.

Fontenot, J., & McMurray, P. (2020). Decolonizing Entry to Practice: Reconceptualizing Methods to Facilitate Diversity in Nursing Programs. *Teaching and Learning in Nursing*, *15*(4), 272–279.

Friedman, G. D., Cutter, G. R., Donahue, R. P., Hughes, G. H., Hulley, S. B., Jacobs David R, J., … Savage, P. J. (1988). CARDIA: Study Design, Recruitment, and Some Characteristics of the Examined Subjects. *Journal of Clinical Epidemiology*, *41*(11), 1105–1116. Retrieved from https://ac.els-cdn.com/0895435688900807/1-s2.0-0895435688900807-main.pdf?_tid=8b551279-e8e3-434c-a9c7-95b89bb73c03&acdnat=1551994503_ee286aa869d2c7dec373ad5b73138216

Gallo, L. C., Bogart, L. M., Vranceanu, A.-M., & Walt, L. C. (2004). Job Characteristics, Occupational Status, and Ambulatory Cardiovascular Activity in Women. *Ann Behav Med*, *28*(1), 62–73. Retrieved from https://academic.oup.com/abm/article-abstract/28/1/62/4633686

Gemkow, S., Neugart, M., Gemkow, S., & Neugart, M. (2011). Referral Hiring, Endogenous Social Networks, and Inequality: An Agent-based Analysis. *J Evol Econ*, *21*, 703–719. https://doi.org/10.1007/s00191-011-0219-3

Geronimus, A. T. (1992). The Weathering Hypothesis and the Health of African-American Women and Infants: Evidence and Speculations. *Ethnicity & Disease*, *2*(3), 207–221. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/1467758

Gilbert-Ouimet, M., Trudel, X., Brisson, C., Milot, A., & Vézina, M. (2014). Adverse Effects of Psychosocial Work Factors on Blood Pressure: Systematic Review of Studies on Demand-control-support and Effort-reward Imbalance Models. *Scandinavian Journal of Work, Environment and Health*, *40*(2), 109–132. https://doi.org/10.5271/sjweh.3390

Grace, M. K., & VanHeuvelen, J. S. (2019). Occupational Variation in Burnout among

Medical Staff: Evidence for the Stress of Higher Status. *Social Science and Medicine*, *232*(December 2017), 199–208. https://doi.org/10.1016/j.socscimed.2019.05.007

Hawkins, D. (2020). Differential Occupational Risk for COVID-19 and Other Infection Exposure According to Race and Ethnicity. *American Journal of Industrial Medicine*, *63*(9), 817–820. https://doi.org/10.1002/ajim.23145

Holahan, J. (2011). The 2007-09 Recession And Health Insurance Coverage. *Health Affairs*, *1*, 145–152. https://doi.org/10.1377/hlthaff.2010.1003

Holzer, Harry; Neumark, D. (1999). Are Affirmative Action Hires Less Qualified? Evidence from Employer-employee Data on New Hires. *Journal of Labor Economics*, *17*(3), 534–569. https://doi.org/10.1017/CBO9781107415324.004

Homan, P. (2019). Structural Sexism and Health in the United States: A New Perspective on Health Inequality and the Gender System. *American Sociological Review*, *84*(3), 486–516. https://doi.org/10.1177/0003122419848723

Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2000). *Applied Logistic Regression* (2nd ed.). Wiley-Interscience Publication.

Jacob, J. A. (2015). AAMC Report Examines How to Increase the Pipeline of Black Men Entering Medical School. *JAMA*, *314*(21), 2222–2224. https://doi.org/10.1001/jama.2015.12005

Johnson, J. V, & Hall, E. M. (1988). Job Strain, Work Place Social Support, and Cardiovascular Disease: A Cross-Sectional Study of a Random Sample of the Swedish Working Population. *American Journal of Public Health*, *78*(10), 1336–1342. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1349434/pdf/amjph00249-0078.pdf

Joseph, N. T., Muldoon, M. F., Manuck, S. B., Matthews, K. A., MacDonald, L. A., Grosch, J., & Kamarck, T. W. (2016). The Role of Occupational Status in the Association Between Job Strain and Ambulatory Blood Pressure During Working and Nonworking Days. *Psychosomatic Medicine*, *78*(8), 940–949. https://doi.org/10.1097/PSY.0000000000000349

Kakani, P., Chandra, A., Mullainathan, S., & Ziad, O. (2020). Allocation of COVID-19

Relief Funding to Disproportionately Black Counties. *JAMA*, *324*(10), 1000–1003. https://doi.org/10.1001/jama.2020.15301

Kalev, A., Kelly, E., & Dobbin, F. (2006). Best Practices or Best Guesses? Assessing the Efficacy of Corporate Affirmative Action and Diversity Policies. *American Sociological Review*, *71*(4), 589–617. Retrieved from https://www-jstor-org.ezp2.lib.umn.edu/stable/pdf/30039011.pdf?refreqid=excelsior%3A188ad8e799862b2b933fb8c6b3c6c809

Kalil, A., Ziol-Guest, K. M., Hawkley, L. C., & Cacioppo, J. T. (2010). Job Insecurity and Change Over Time in Health among Older Men and Women. *Journals of Gerontology - Series B Psychological Sciences and Social Sciences*, *65 B*(1), 81–90. https://doi.org/10.1093/geronb/gbp100

Kambhampati, A. K., O, A. C., Whitaker, M., Magill, S. S., Chea, N., Chai, S. J., … Kim, L. (2020). COVID-19–Associated Hospitalizations Among Health Care Personnel -- COVID-NET, 13 States, March 1–May 31, 2020. *Morbidity and Mortality Weekly Report*, *69*(43), 1576–1583. Retrieved from https://www.cdc.gov/coronavirus/2019-ncov/covid-data/covidview/purpose-

Kaplan, G. A. (2017). *Growing Inequality: Bridging Complex Systems, Population Health, and Health Disparities*. (A. V. Diez-Roux, C. P. Simon, & S. Galea, Eds.). Westphalia Press.

Karasek, R. A. (1979). Job Demand, Job Decision Latitude, and Mental Strain: Implications for Job Redesign. *Administrative Science Quarterly*, *24*(2), 285–308. Retrieved from https://about.jstor.org/terms

Karasek, R., Brisson, C., Kawakami, N., Houtman, I., Bongers, P., & Amick, B. (1998). The Job Content Questionnaire (JCQ): An Instrument for Internationally Comparative Assessments of Psychosocial Job Characteristics. *Journal of Occupational Health Psychology*, *3*(4), 322–355. https://doi.org/10.1037/1076-8998.3.4.322

Kaur, H., Luckhaupt, S. E., Li, J., Alterman, T., & Calvert, G. M. (2014). Workplace Psychosocial Factors Associated with Hypertension in the U.S. Workforce: A Cross-sectional Study Based on the 2010 National Health Interview Survey. *American*

Journal of Industrial Medicine, *57*(9), 1011–1021. https://doi.org/10.1002/ajim.22345

Kirkland, E. B., Heincelman, M., Bishu, K. G., Schumann, S. O., Schreiner, A., Axon, ; R Neal, … Moran, W. P. (2018). Trends in Healthcare Expenditures among US Adults with Hypertension: National Estimates, 2003-2014. *Journal of the American Heart Association*, *7*, e008731. https://doi.org/10.1161/JAHA.118.008731

Kochhar, R. (2012). *A Recovery No Better than the Recession: Median Household Income, 2007 to 2011*. Washington, DC. Retrieved from http://www.federalreserve.gov/pubs/bulletin/2012/PDF/scf12.pdf

Kressin, N. R., Terrin, N., Hanchate, A. D., Price, L. L., Moreno-Koehler, A., Leclair, A., … Freund, K. M. (2020). Is Insurance Instability Associated with Hypertension Outcomes and Does This Vary by Race/ethnicity? *BMC Health Services Research*, *20*(16). https://doi.org/10.1186/s12913-020-05095-8

Krieger, N., Chen, J. T., Waterman, P. D., Hartman, C., Stoddard, A. M., Quinn, M. M., … Youngstrom, R. (2008). The Inverse Hazard Law: Blood Pressure, Sexual Harassment, Racial Discrimination, Workplace Abuse and Occupational Exposures in US Low-income Black, White and Latino Workers. *Social Science & Medicine*, *67*, 1970–1981. https://doi.org/10.1016/j.socscimed.2008.09.039

Kshirsagar, A. V, Chiu, Y.-L., Bomback, A. S., August, P. A., Viera, A. J., Colindres, R. E., & Bang, H. (2010). A Hypertension Risk Score for Middle-aged and Older Adults. *Journal of Clinical Hypertension (Greenwich, Conn.)*, *12*(10), 800–808. https://doi.org/10.1111/j.1751-7176.2010.00343.x

Kurtulus, F. A. (2016). The Impact of Affirmative Action on The Employment of Minorities and Women: A Longitudinal Analysis Using Three Decades of EEO-1 Filings. *Journal of Policy Analysis and Management*, *35*(1), 34–66. https://doi.org/10.1002/pam

Kwak, L., Berrigan, D., Van Domelen, D., Sjöström, M., & Hagströmer, M. (2016). Examining Differences in Physical Activity Levels by Employment Status and/or Job Activity Level: Gender-specific Comparisons between the United States and Sweden. *Journal of Science and Medicine in Sport*, *19*, 482–487.

https://doi.org/10.1016/j.jsams.2015.05.008

Landsbergis, P. A., Diez-Roux, A. V, Fujishiro, K., Baron, S., Kaufman, J. D., Meyer, J. D., … Szklo, M. (2015). Job Strain, Occupational Category, Systolic Blood Pressure, and Hypertension Prevalence: The Multi-Ethnic Study of Atherosclerosis. *Journal of Occupational and Environmental Medicine*, *57*(11), 1178–1184. https://doi.org/10.1097/JOM.0000000000000533

Lee, D. J., Fleming, L. E., LeBlanc, W. G., Arheart, K. L., Ferraro, K. F., Pitt-Catsouphes, M., … Kachan, D. (2012). Health Status and Risk Indicator Trends of the Aging US Health Care Workforce. *Journal of Occupational and Environmental Medicine*, *54*(4), 497–503. https://doi.org/10.1097/JOM.0b013e318247a379

Levenstein, S., Smith, M. W., & Kaplan, G. A. (2001). Psychosocial Predictors of Hypertension in Men and Women. *Archives of Internal Medicine*, *161*(10), 1341–1346. https://doi.org/10.1001/archinte.161.10.1341

Light, K. C., Turner, J. R., & Hinderliter, A. L. (1992). Job Strain and Ambulatory Work Blood Pressure in Healthy Young Men and Women. *Hypertension*, *20*, 214–218. Retrieved from http://ahajournals.org

Lipscomb, H. J., Loomis, D., Mcdonald, M. A., Argue, R. A., & Wing, S. (2006). A Conceptual Model of Work and Health Disparities in United States. *International Journal of Health Services*, *36*(1), 25–50. Retrieved from https://journals.sagepub.com/doi/pdf/10.2190/BRED-NRJ7-3LV7-2QCG

Luke, D. A., & Stamatakis, K. A. (2012). Systems Science Methods in Public Health: Dynamics, Networks, and Agents. *Annu. Rev. Public Health*, *33*, 357–376. https://doi.org/10.1146/annurev-publhealth-031210-101222

Macy, M. W., & Willer, R. (2002). From Factors to Actors: Computational Sociology and Agent-Based Modeling I. *Annu. Rev. Sociol*, *28*, 143–166. https://doi.org/10.1146/annurev.soc.28.110601.141117

Malat, J., Mayorga-Gallo, S., & Williams, D. R. (2018). The Effects of Whiteness on The Health of Whites in the USA. *Social Science & Medicine*, *199*, 148–156. https://doi.org/10.1016/j.socscimed.2017.06.034

Marmot, M., Smith, G., Stansfeld, S., Patel, C., North, F., Head, J., … Feeney, A. (1991).

Health Inequalities among British Civil Servants: the Whitehall II Study. *Lancet*, *337*(8754), 1387–1393. https://doi.org/10.1016/0140-6736(91)93068-K

Marovich, S., Mobley, A., & Groenewold, M. (2020). Making Industry and Occupation Information Useful for Public Health: A Guide to Coding Industry and Iccupation Text Fields. Retrieved January 11, 2019, from https://blogs.cdc.gov/niosh-science-blog/2020/06/17/industry-occup-coding/

Marshall, B. D. L., & Galea, S. (2015). Formalizing the Role of Agent-Based Modeling in Causal Inference and Epidemiology. *American Journal of Epidemiology*, *181*(2), 92–99. https://doi.org/10.1093/aje/kwu274

Matthay, E., Duchowny, K., Riley, A., & Galea, S. (2021). Projected All-Cause Deaths Attributable to COVID-19-Related Unemployment in the United States. *American Journal of Public Health*, *111*(4), 696–699. https://doi.org/10.2105/AJPH.2020.306095

McCluney, C. L., Schmitz, L. L., Hicken, M. T., & Sonnega, A. (2018). Structural Racism in the Workplace: Does Perception Matter for Health Inequalities? *Social Science and Medicine*, *199*, 106–114. https://doi.org/10.1016/j.socscimed.2017.05.039

McClure, E. S., Vasudevan, P., Bailey, Z., Patel, S., & Robinson, W. R. (2020). Racial Capitalism Within Public Health—How Occupational Settings Drive Covid-19 Disparities. *American Journal of Epidemiology*, *189*(11), 1244–1253. https://doi.org/10.1093/aje/kwaa126

Merchant, J. L., & Omary, M. B. (2010). Underrepresentation of Underrepresented Minorities in Academic Medicine: The Need to Enhance the Pipeline and the Pipe. *Gastroenterology*, *138*, 19–26. https://doi.org/10.1053/j.gastro.2009.11.017

Meyer, J. D. (2014). Race-based Job Discrimination, Disparities in Job Control, and Their Joint Effects on Health. *American Journal of Industrial Medicine*, *57*(5), 587–595. https://doi.org/10.1002/ajim.22255

Meyer, P. B., & Osborne, A. M. (2005). Proposed Category System for 1960-2000 Census Occupations. *BLS Working Papers*, (September), 1–67.

National Crosswalk Service Center – Training Module – WIDCenter. (n.d.). Retrieved

March 29, 2019, from http://www.widcenter.org/national-crosswalk-service-center/

National Institute for Occupational Safety and Health. (2019). CDC - NIOSH Worker Health Charts. Retrieved December 2, 2019, from https://wwwn.cdc.gov/NIOSH-WHC/chart/nhis-chronic?OU=HYPEV&T=R&V=R

Neath, A. A., & Cavanaugh, J. E. (2012). The Bayesian Information Criterion: Background, Derivation, and Applications. *Wiley Interdisciplinary Reviews: Computational Statistics*, *4*(2), 199–203. https://doi.org/10.1002/wics.199

Neugart, M. (2004). *Endogenous Matching Functions: An agent-based Computational Approach*. Retrieved from https://pdfs.semanticscholar.org/87bc/7d5a7e98ba4431a71a32bd0f72c5f37122df.pdf

Nygren, K., Hammarström, A., & Gong, W. (2015). Is Hypertension in Adult Age related to Unemployment at a Young Age? Results from the Northern Swedish Cohort. *Scandinavian Journal of Public Health*, *43*(1), 52–58. https://doi.org/10.1177/1403494814560845

O*NET Resource Center. (2019). O*NET Resource Center. Retrieved July 9, 2019, from https://www.onetcenter.org/

Occupational Safety and Health Administration. (2021). COVID-19 - Control and Prevention - Healthcare Workers and Employers. Retrieved August 16, 2021, from https://www.osha.gov/coronavirus/control-prevention/healthcare-workers

Pager, D., Bonikowski, B., & Western, B. (2009). *Discrimination in a Low-Wage Labor Market: A Field Experiment*. *American Sociological Review* (Vol. 74). Retrieved from https://www-jstor-org.ezp2.lib.umn.edu/stable/pdf/27736094.pdf?refreqid=excelsior%3A6671044ad73caa4991b581f0a9247900

Parikh, N. I., Pencina, M. J., Wang, T. J., Benjamin, E. J., Lanier, K. J., Levy, D., … Vasan, R. S. (2008). A Risk Score for Predicting Near-Term Incidence of Hypertension: The Framingham Heart Study. *Annals of Internal Medicine*, *148*(2), 102. https://doi.org/10.7326/0003-4819-148-2-200801150-00005

Paynter, N. P., Cook, N. R., Everett, B. M., Sesso, H. D., Buring, J. E., & Ridker, P. M.

(2009). Prediction of Incident Hypertension Risk in Women with Currently Normal Blood Pressure. *The American Journal of Medicine*, *122*(5), 464–471. https://doi.org/10.1016/j.amjmed.2008.10.034

Pedulla, D. S., & Pager, D. (2019). Race and Networks in the Job Search Process. *American Sociological Review*, *84*(6), 983–1012. https://doi.org/10.1177/0003122419883255

Phelan, J. C., & Link, B. G. (2015). Is Racism a Fundamental Cause of Inequalities in Health? *Annu. Rev. Sociol*, *41*, 311–330. https://doi.org/10.1146/annurev-soc-073014-112305

Quillian, L., Pager, D., Hexel, O., & Midtbøen, A. H. (2017). Meta-analysis of Field Experiments Shows No Change in Racial Discrimination in Hiring Over Time. *Proceedings of the National Academy of Sciences*, *114*(41), 10870–10875. https://doi.org/10.1073/pnas.1706255114

Ray, V. (2019). A Theory of Racialized Organizations. *American Sociological Review*, *84*(1), 26–53. https://doi.org/10.1177/0003122418822335

Reitsma, M. B., Claypool, A. L., Vargo, J., Shete, P. B., McCorvie, R., Wheeler, W. H., … Goldhaber-Fiebert, J. D. (2021). Racial/Ethnic Disparities In COVID-19 Exposure Risk, Testing, And Cases At The Subcounty Level In California. *Health Affairs*, 10.1377/hlthaff. https://doi.org/10.1377/hlthaff.2021.00098

Roberts, D. E. (2020). The Art of Medicine: Abolish Race Correction. *Lancet*, *397*, 17–18. https://doi.org/10.1016/S0140-6736(20)32716-1

Robinson, C. J. (2000). *Black Marxism* (2nd ed.). University of North Carolina Press.

Ruggles, S., Flood, S., Goeken, R., Grover, J., Meyer, E., Pacas, J., & Sobek., M. (2020). IPUMS USA. Minneapolis, MN. Retrieved from https://doi.org/10.18128/D010.V9.0

Samanic, C. M., Barbour, K. E., Liu, Y., Fang, J., Lu, H., Schieb, L., & Greenlund, K. J. (2020). Prevalence of Self-Reported Hypertension and Antihypertensive Medication Use Among Adults-United States, 2017. *Morbidity and Mortality Weekly Report*, *69*(14), 393–398. Retrieved from https://www.cdc.gov/mmwr/mmwr_continuingEducation.html

Siebert, U., Alagoz, O., Bayoumi, A. M., Jahn, B., Owens, D. K., Cohen, D. J., … Briggs, A. H. (2012). State-Transition Modeling: A Report of the ISPOR-SMDM Modeling Good Research Practices Task Force-3. *Medical Decision Making*, *32*, 690–700. https://doi.org/10.1177/0272989X12455463

Siebert, U., Alagoz, O., Bayoumi, A. M., Jahn, B., Owens, D. K., Cohen, D. J., & Kuntz, K. M. (2012). State-Transition Modeling: A Report of the ISPOR-SMDM Modeling Good Research Practices Task Force-3 Background to the Task Force. https://doi.org/10.1016/j.jval.2012.06.014

Smed, S., Tetens, I., Lund, T. B., Holm, L., & Nielsen, A. L. (2017). The Consequences of Unemployment on Diet Composition and Purchase Behaviour: A Longitudinal Study from Denmark. *Public Health Nutrition*, *21*(3), 580–592. https://doi.org/10.1017/S136898001700266X

Smedley, A., & Smedley, B. D. (2005). Race as Biology Is Fiction, Racism As a Social Problem Is Real : Anthropological and Historical Perspectives on the Social Construction of Race. *American Psychologist*, *60*(1), 16–26. https://doi.org/10.1037/0003-066X.60.1.16

Smith, T. E., & Zenou, Y. (2003). A Discrete-Time Stochastic Model of Job Matching. *Review of Economic Dynamics*, *6*, 54–79. https://doi.org/10.1016/S1094-2025(02)00007-8

Sun, D., Liu, J., Xiao, L., Liu, Y., Wang, Z., Li, C., … Wen, S. (2017). Recent Development of Risk-prediction Models for Incident Hypertension: An Updated Systematic Review. *PLoS ONE*, *12*(10), e0187240. https://doi.org/10.1371/journal.pone.0187240

Tassier, T., & Menczer, F. (2008). Social Network Structure, Segregation, and Equality in a Labor Market with Referral Hiring. *Journal of Economic Behavior & Organization*, *66*(3–4), 514–528. https://doi.org/10.1016/j.jebo.2006.07.003

Unmuessig, V., Fishman, P. A., Vrijhoef, H. J. M., Elissen, A. M. J., & Grossman, D. C. (2016). Association of Controlled and Uncontrolled Hypertension With Workplace Productivity. *J Clin Hypertens (Green-Wich)*, *18*, 217–222. https://doi.org/10.1111/jch.12648

Van Domelen, D. R., Koster, A., Caserotti, P., Brychta, R. J., Chen, K. Y., Mcclain, J. J., … Harris, T. B. (2011). Employment and Physical Activity in the U.S. *Am J Prev Med*, *41*(2), 136–145. https://doi.org/10.1016/j.amepre.2011.03.019

Vanni, T., Karnon, J., Madan, J., White, R. G., Edmunds, W. J., Foss, A. M., & Legood, R. (2011). Calibrating Models in Economic Evaluation A Seven-Step Approach. *PharmacoEconomics*, *29*(1), 35–49. Retrieved from http://links.adisonline.com/PCZ/

Vyas, D. A., Eisenstein, L. G., & Jones, D. S. (2020). Hidden in Plain Sight — Reconsidering the Use of Race Correction in Clinical Algorithms. *New England Journal of Medicine*, *383*(9), 874–882. https://doi.org/10.1056/nejmms2004740

Wingfield, A. H. (2019). *Flatlining: Race, Work, and Health Care in the New Economy* (1st ed.). University of California Press.

Wingfield, A. H., & Chavez, K. (2020). Getting In, Getting Hired, Getting Sideways Looks: Organizational Hierarchy and Perceptions of Racial Discrimination. *American Sociological Review*, *85*(1), 31–57. https://doi.org/10.1177/0003122419894335

Wingfield, A. H., & Wingfield, J. H. (2014). When Visibility Hurts and Helps: How Intersections of Race and Gender Shape Black Professional Men's Experiences with Tokenization. *Cultural Diversity and Ethnic Minority Psychology*, *20*(4), 483–490. https://doi.org/10.1037/a0035761

Wozniak, M. (2016). *Job Placement Agencies in an Agent-based Model of the Local Labor Market with the Long-term Unemployed and On-the-job Flows*. Retrieved from http://www.economics-ejournal.org/economics/journalarticles/2016-29

Yearby, R. (2018). Racial Disparities in Health Status and Access to Healthcare: The Continuation of Inequality in the United States Due to Structural Racism. *American Journal of Economics and Sociology*, *77*(3–4), 1113–1152. https://doi.org/10.1111/ajes.12230

APPENDIXES

APPENDIX 1: Psychosocial Work Environment Measures, Indexed by the 2000 Standard Occupational Classification (SOC)

SOC-2000	Occupation Title	Job Demand (0-4)	Job Control (0-4)	Support (0-2)
11-1011	Chief Executives	2.161	3.360	0.949
11-2011	Advertising and Promotions Managers	2.386	3.074	1.050
11-2021	Marketing Managers	2.327	3.148	1.100
11-2022	Sales Managers	1.893	2.924	1.124
11-3011	Administrative Services Managers	1.743	2.824	1.148
11-3021	Computer and Information Systems Managers	2.219	3.098	1.074
11-3031	Financial Managers	2.057	2.998	1.237
11-3040	Human Resources Managers	1.914	3.174	1.124
11-3041	Compensation and Benefits Managers	1.914	3.174	1.124
11-3042	Training and Development Managers	1.691	2.824	1.250
11-3051	Industrial Production Managers	1.832	3.248	1.248
11-3061	Purchasing Managers	2.457	2.674	1.174
11-3071	Transportation, Storage, and Distribution Managers	2.080	3.085	1.312
11-9011	Farm, Ranch, and Other Agricultural Managers	1.438	3.147	1.008
11-9012	Farmers and Ranchers	1.600	3.174	0.500
11-9021	Construction Managers	2.023	2.996	0.998

11-9031	Education Administrators, Preschool and Child Care Center/Program	1.757	3.074	1.148
11-9032	Education Administrators, Elementary and Secondary School	1.757	3.074	1.148
11-9033	Education Administrators, Postsecondary	1.809	3.198	1.048
11-9041	Engineering Managers	2.461	3.174	0.950
11-9051	Food Service Managers	1.532	3.148	1.148
11-9061	Funeral Directors	1.389	2.698	0.924
11-9071	Gaming Managers	1.720	2.824	1.174
11-9081	Lodging Managers	1.900	2.922	1.050
11-9111	Medical and Health Services Managers	1.737	2.998	1.048
11-9121	Natural Sciences Managers	1.823	3.124	0.974
11-9131	Postmasters and Mail Superintendents	1.840	2.598	1.224
11-9141	Property, Real Estate, and Community Association Managers	1.640	2.974	0.998
11-9151	Social and Community Service Managers	1.720	3.046	1.200
13-1011	Agents and Business Managers of Artists, Performers, and Athletes	2.120	2.998	0.798
13-1021	Purchasing Agents and Buyers, Farm Products	1.594	2.722	1.124
13-1022	Wholesale and Retail Buyers, Except Farm Products	1.846	2.722	1.274

13-1023	Purchasing Agents, Except Wholesale, Retail, and Farm Products	1.857	2.648	1.200
13-1031	Claims Adjusters, Examiners, and Investigators	2.180	2.486	1.411
13-1032	Insurance Appraisers, Auto Damage	1.480	2.474	1.374
13-1041	Compliance Officers, Except Agriculture, Construction, Health and Safety, and Transportation	1.965	2.531	1.299
13-1051	Cost Estimators	2.703	2.498	1.224
13-1071	Employment, Recruitment, and Placement Specialists	1.549	2.460	1.336
13-1072	Compensation, Benefits, and Job Analysis Specialists	1.440	2.824	1.150
13-1073	Training and Development Specialists	1.457	2.974	1.248
13-1111	Management Analysts	1.680	3.200	1.124
13-1121	Meeting and Convention Planners	1.554	2.972	1.074
13-2011	Accountants and Auditors	1.979	2.685	1.175
13-2021	Appraisers and Assessors of Real Estate	1.951	2.673	1.212
13-2031	Budget Analysts	2.103	2.598	1.300
13-2041	Credit Analysts	1.709	2.398	1.374
13-2051	Financial Analysts	2.061	3.248	1.200
13-2052	Personal Financial Advisors	1.829	2.574	1.248
13-2053	Insurance Underwriters	2.349	2.374	1.398
13-2061	Financial Examiners	1.857	2.798	1.200

13-2071	Loan Counselors	1.771	2.424	1.300
13-2072	Loan Officers	1.771	2.424	1.300
13-2081	Tax Examiners, Collectors, and Revenue Agents	1.789	2.448	1.400
13-2082	Tax Preparers	1.989	2.198	1.274
15-1021	Computer Programmers	2.251	3.198	1.324
15-1031	Computer Software Engineers, Applications	1.894	3.522	1.150
15-1032	Computer Software Engineers, Systems Software	1.894	3.522	1.150
15-1041	Computer Support Specialists	2.103	2.974	1.374
15-1051	Computer Systems Analysts	1.851	3.322	1.300
15-1061	Database Administrators	1.829	3.022	1.274
15-1071	Network and Computer Systems Administrators	2.257	3.174	1.100
15-1081	Network Systems and Data Communications Analysts	2.309	2.996	1.250
15-2011	Actuaries	1.643	2.874	1.250
15-2021	Mathematicians	2.503	3.498	0.974
15-2031	Operations Research Analysts	1.954	3.498	1.098
15-2041	Statisticians	2.364	3.422	1.050
15-2091	Mathematical Technicians	1.657	2.648	1.298
17-1011	Architects, Except Landscape and Naval	2.280	3.498	0.900
17-1012	Landscape Architects	1.571	3.298	0.974
17-1021	Cartographers and Photogrammetrists	1.777	3.196	0.848

17-1022	Surveyors	2.166	2.924	1.098
17-2011	Aerospace Engineers	2.091	3.574	1.024
17-2021	Agricultural Engineers	1.757	3.422	1.100
17-2041	Chemical Engineers	2.061	3.422	1.100
17-2051	Civil Engineers	2.617	3.324	1.148
17-2061	Computer Hardware Engineers	1.894	3.522	1.150
17-2071	Electrical Engineers	1.897	3.424	1.148
17-2072	Electronics Engineers, Except Computer	1.966	3.424	1.074
17-2111	Health and Safety Engineers, Except Mining Safety Engineers and Inspectors	2.339	3.256	1.199
17-2112	Industrial Engineers	2.137	3.424	1.124
17-2121	Marine Engineers and Naval Architects	1.996	3.448	1.023
17-2131	Materials Engineers	1.817	3.224	1.074
17-2141	Mechanical Engineers	2.061	3.474	1.098
17-2151	Mining and Geological Engineers, Including Mining Safety Engineers	2.021	3.322	1.100
17-2161	Nuclear Engineers	3.086	3.372	1.124
17-2171	Petroleum Engineers	2.023	3.298	1.100
17-3011	Architectural and Civil Drafters	1.929	2.574	1.150
17-3012	Electrical and Electronics Drafters	1.878	2.798	1.174

17-3013	Mechanical Drafters	1.880	2.698	1.200
17-3021	Aerospace Engineering and Operations Technicians	2.406	2.598	1.224
17-3022	Civil Engineering Technicians	1.771	2.372	1.374
17-3023	Electrical and Electronic Engineering Technicians	1.712	2.381	1.325
17-3024	Electro-Mechanical Technicians	2.777	2.272	1.324
17-3026	Industrial Engineering Technicians	1.750	2.474	1.424
17-3027	Mechanical Engineering Technicians	2.223	2.498	1.400
17-3031	Surveying and Mapping Technicians	1.809	2.411	1.250
19-1011	Animal Scientists	2.154	3.248	0.950
19-1012	Food Scientists and Technologists	1.389	3.198	1.048
19-1013	Soil and Plant Scientists	1.814	3.249	0.875
19-1020	Biological Scientists	1.840	3.424	0.898
19-1021	Biochemists and Biophysicists	1.909	3.548	0.874
19-1022	Microbiologists	1.869	3.222	1.024
19-1023	Zoologists and Wildlife Biologists	1.674	3.222	1.000
19-1031	Conservation Scientists	1.652	3.073	1.040
19-1032	Foresters	1.486	3.124	1.024
19-1041	Epidemiologists	2.051	3.472	0.948
19-1042	Medical Scientists, Except Epidemiologists	2.051	3.472	0.948
19-2011	Astronomers	2.280	3.472	0.774

19-2012	Physicists	1.663	3.624	0.924
19-2021	Atmospheric and Space Scientists	1.457	3.024	1.074
19-2031	Chemists	2.394	3.524	1.100
19-2032	Materials Scientists	1.794	3.296	1.074
19-2041	Environmental Scientists and Specialists, Including Health	1.800	3.324	0.974
19-2042	Geoscientists, Except Hydrologists and Geographers	1.811	3.348	0.874
19-2043	Hydrologists	1.606	3.396	0.874
19-3011	Economists	2.194	3.372	1.000
19-3021	Market Research Analysts	1.594	2.898	1.100
19-3031	Clinical, Counseling, and School Psychologists	2.042	3.631	0.691
19-3032	Industrial-Organizational Psychologists	1.817	3.324	0.900
19-3041	Sociologists	1.417	3.398	0.874
19-3051	Urban and Regional Planners	1.479	3.224	1.148
19-3091	Anthropologists and Archeologists	1.480	3.361	0.750
19-3092	Geographers	1.589	3.124	0.950
19-3093	Historians	1.549	3.248	0.824
19-3094	Political Scientists	1.343	3.272	0.724
19-4011	Agricultural and Food Science Technicians	1.931	2.173	1.274
19-4021	Biological Technicians	2.080	2.024	1.274

19-4031	Chemical Technicians	1.714	2.398	1.324
19-4041	Geological and Petroleum Technicians	1.717	2.461	1.287
19-4051	Nuclear Technicians	2.057	2.536	1.450
19-4061	Social Science Research Assistants	2.343	2.024	1.374
19-4091	Environmental Science and Protection Technicians, Including Health	1.829	2.698	1.274
19-4092	Forensic Science Technicians	1.949	2.998	1.274
21-1011	Substance Abuse and Behavioral Disorder Counselors	1.629	3.098	1.124
21-1012	Educational, Vocational, and School Counselors	2.097	2.996	1.074
21-1014	Mental Health Counselors	1.629	3.098	1.124
21-1021	Child, Family, and School Social Workers	2.194	2.972	1.224
21-1022	Medical and Public Health Social Workers	1.629	3.098	1.124
21-1023	Mental Health and Substance Abuse Social Workers	1.629	3.098	1.124
21-1091	Health Educators	2.086	2.974	1.148
21-1092	Probation Officers and Correctional Treatment Specialists	1.709	2.572	1.274
21-1093	Social and Human Service Assistants	1.434	2.398	1.374
21-2011	Clergy	1.240	3.200	0.574
21-2021	Directors, Religious Activities and Education	1.486	3.000	0.824
23-1011	Lawyers	1.983	3.524	0.724

23-1021	Administrative Law Judges, Adjudicators, and Hearing Officers	1.743	2.974	0.898
23-1022	Arbitrators, Mediators, and Conciliators	1.743	2.974	0.898
23-1023	Judges, Magistrate Judges, and Magistrates	2.450	3.398	0.624
23-2011	Paralegals and Legal Assistants	2.526	2.572	1.174
23-2092	Law Clerks	1.789	2.348	1.274
23-2093	Title Examiners, Abstractors, and Searchers	1.525	2.398	1.337
25-1021	Computer Science Teachers, Postsecondary	2.536	3.398	0.998
25-1022	Mathematical Science Teachers, Postsecondary	1.411	3.374	0.998
25-1032	Engineering Teachers, Postsecondary	1.589	3.424	0.998
25-1041	Agricultural Sciences Teachers, Postsecondary	2.726	3.346	0.998
25-1042	Biological Science Teachers, Postsecondary	2.726	3.346	0.998
25-1043	Forestry and Conservation Science Teachers, Postsecondary	2.726	3.346	0.998
25-1052	Chemistry Teachers, Postsecondary	2.164	3.372	0.998
25-1054	Physics Teachers, Postsecondary	1.257	3.372	0.998
25-1061	Anthropology and Archeology Teachers, Postsecondary	1.417	3.398	0.998
25-1062	Area, Ethnic, and Cultural Studies Teachers, Postsecondary	1.417	3.398	0.998

25-1063	Economics Teachers, Postsecondary	1.417	3.398	0.998
25-1065	Political Science Teachers, Postsecondary	1.417	3.398	0.998
25-1066	Psychology Teachers, Postsecondary	1.417	3.398	0.998
25-1067	Sociology Teachers, Postsecondary	1.417	3.398	0.998
25-1071	Health Specialties Teachers, Postsecondary	1.394	3.398	0.998
25-1072	Nursing Instructors and Teachers, Postsecondary	1.980	3.298	1.124
25-1121	Art, Drama, and Music Teachers, Postsecondary	1.400	3.398	0.998
25-1123	English Language and Literature Teachers, Postsecondary	2.000	3.348	0.998
25-1124	Foreign Language and Literature Teachers, Postsecondary	2.000	3.348	0.998
25-1125	History Teachers, Postsecondary	1.417	3.398	0.998
25-1191	Graduate Teaching Assistants	1.331	2.672	1.300
25-1194	Vocational Education Teachers Postsecondary	1.566	3.196	1.074
25-2011	Preschool Teachers, Except Special Education	1.357	3.222	1.098
25-2012	Kindergarten Teachers, Except Special Education	1.146	3.222	1.098
25-2021	Elementary School Teachers, Except Special Education	1.365	3.274	1.098
25-2022	Middle School Teachers, Except Special and Vocational Education	2.023	3.298	1.098
25-2023	Vocational Education Teachers, Middle School	2.023	3.298	1.098

25-2031	Secondary School Teachers, Except Special and Vocational Education	2.023	3.298	1.098
25-2032	Vocational Education Teachers, Secondary School	2.023	3.298	1.098
25-2041	Special Education Teachers, Preschool, Kindergarten, and Elementary School	1.400	3.298	1.098
25-2042	Special Education Teachers, Middle School	1.400	3.298	1.098
25-2043	Special Education Teachers, Secondary School	1.400	3.298	1.098
25-3011	Adult Literacy, Remedial Education, and GED Teachers and Instructors	1.823	3.272	1.098
25-3021	Self-Enrichment Education Teachers	1.823	3.272	1.098
25-4011	Archivists	2.423	2.948	1.124
25-4012	Curators	1.994	3.022	1.048
25-4013	Museum Technicians and Conservators	1.960	2.722	1.224
25-4021	Librarians	1.833	2.972	1.098
25-4031	Library Technicians	1.509	2.274	1.324
25-9011	Audio-Visual Collections Specialists	1.743	2.848	1.174
25-9021	Farm and Home Management Advisors	1.280	3.122	1.124
25-9031	Instructional Coordinators	2.823	3.298	1.074
25-9041	Teacher Assistants	1.263	2.098	1.374
27-1011	Art Directors	2.034	3.698	0.974

27-1013	Fine Artists, Including Painters, Sculptors, and Illustrators	1.241	3.542	0.718
27-1021	Commercial and Industrial Designers	1.760	3.472	1.174
27-1022	Fashion Designers	1.474	3.624	1.048
27-1023	Floral Designers	1.771	3.198	1.048
27-1024	Graphic Designers	1.240	3.398	1.048
27-1025	Interior Designers	1.789	3.546	0.824
27-1026	Merchandise Displayers and Window Trimmers	1.150	3.148	1.098
27-1027	Set and Exhibit Designers	1.597	3.435	1.011
27-2011	Actors	1.469	3.172	0.724
27-2012	Producers and Directors	1.609	3.383	0.949
27-2021	Athletes and Sports Competitors	1.349	2.522	1.398
27-2022	Coaches and Scouts	1.971	3.098	1.048
27-2023	Umpires, Referees, and Other Sports Officials	1.760	2.798	1.148
27-2031	Dancers	1.343	2.974	0.674
27-2032	Choreographers	1.349	3.648	0.850
27-2041	Music Directors and Composers	1.215	3.673	0.707
27-2042	Musicians and Singers	1.827	3.149	0.712
27-3011	Radio and Television Announcers	1.577	2.874	1.224
27-3012	Public Address System and Other Announcers	1.177	2.672	1.200

27-3021	Broadcast News Analysts	1.531	2.998	1.200
27-3022	Reporters and Correspondents	1.891	2.948	1.224
27-3031	Public Relations Specialists	1.377	3.198	1.100
27-3041	Editors	1.811	3.474	1.198
27-3042	Technical Writers	1.486	3.174	1.224
27-3043	Writers and Authors	1.674	3.249	0.943
27-3091	Interpreters and Translators	1.749	2.422	0.924
27-4011	Audio and Video Equipment Technicians	1.743	2.848	1.174
27-4012	Broadcast Technicians	1.760	2.548	1.324
27-4013	Radio Operators	1.760	2.300	1.374
27-4014	Sound Engineering Technicians	2.503	2.598	1.174
27-4021	Photographers	1.740	3.311	0.911
27-4031	Camera Operators, Television, Video, and Motion Picture	1.429	2.774	1.250
27-4032	Film and Video Editors	2.093	3.072	1.074
29-1011	Chiropractors	2.571	3.648	0.600
29-1021	Dentists, General	2.057	3.548	0.574
29-1022	Oral and Maxillofacial Surgeons	2.171	3.598	0.724
29-1023	Orthodontists	2.469	3.572	0.624
29-1024	Prosthodontists	1.989	3.474	0.674

29-1031	Dietitians and Nutritionists	2.137	3.098	1.000
29-1041	Optometrists	1.920	3.548	0.700
29-1051	Pharmacists	2.217	3.000	0.898
29-1061	Anesthesiologists	2.234	3.124	0.948
29-1062	Family and General Practitioners	2.286	3.648	0.774
29-1063	Internists, General	2.286	3.648	0.774
29-1064	Obstetricians and Gynecologists	2.286	3.648	0.774
29-1065	Pediatricians, General	2.286	3.648	0.774
29-1066	Psychiatrists	2.109	3.672	0.624
29-1067	Surgeons	2.771	3.600	0.874
29-1071	Physician Assistants	2.063	2.574	1.024
29-1081	Podiatrists	2.507	3.674	0.648
29-1111	Registered Nurses	2.180	2.622	1.024
29-1121	Audiologists	1.543	3.298	1.024
29-1122	Occupational Therapists	1.463	3.148	1.048
29-1123	Physical Therapists	1.789	3.198	1.000
29-1124	Radiation Therapists	2.246	2.196	1.174
29-1125	Recreational Therapists	1.886	3.124	1.124
29-1126	Respiratory Therapists	3.126	2.572	1.098
29-1127	Speech-Language Pathologists	1.543	3.298	1.024

29-1131	Veterinarians	1.864	3.724	0.600
29-2011	Medical and Clinical Laboratory Technologists	2.043	2.600	1.148
29-2012	Medical and Clinical Laboratory Technicians	2.114	2.146	1.198
29-2021	Dental Hygienists	1.829	2.150	0.974
29-2031	Cardiovascular Technologists and Technicians	2.691	2.348	1.150
29-2033	Nuclear Medicine Technologists	2.229	2.472	1.100
29-2034	Radiologic Technologists and Technicians	2.280	2.348	1.112
29-2041	Emergency Medical Technicians and Paramedics	2.286	2.598	1.200
29-2051	Dietetic Technicians	2.114	2.374	1.250
29-2052	Pharmacy Technicians	2.046	1.772	1.174
29-2053	Psychiatric Technicians	1.737	2.074	1.348
29-2055	Surgical Technologists	2.486	1.724	1.274
29-2061	Licensed Practical and Licensed Vocational Nurses	2.120	2.148	1.074
29-2071	Medical Records and Health Information Technicians	1.909	1.998	1.250
29-2081	Opticians, Dispensing	1.817	3.022	0.900
29-2091	Orthotists and Prosthetists	1.880	2.848	1.174
29-9011	Occupational Health and Safety Specialists	1.800	3.048	1.098
29-9091	Athletic Trainers	2.823	2.798	1.124
31-1011	Home Health Aides	1.623	1.824	0.948
31-1012	Nursing Aides, Orderlies, and Attendants	1.846	1.348	1.298

31-1013	Psychiatric Aides	1.543	1.572	1.324
31-2011	Occupational Therapist Assistants	1.474	1.972	1.324
31-2012	Occupational Therapist Aides	1.474	1.972	1.324
31-2021	Physical Therapist Assistants	2.223	1.922	1.298
31-2022	Physical Therapist Aides	2.223	1.922	1.298
31-9091	Dental Assistants	2.451	1.798	1.224
31-9092	Medical Assistants	2.075	1.698	1.250
31-9093	Medical Equipment Preparers	2.211	1.574	1.348
31-9096	Veterinary Assistants and Laboratory Animal Caretakers	1.536	1.672	1.150
33-1012	First-Line Supervisors/Managers of Police and Detectives	2.309	3.198	1.274
33-1021	First-Line Supervisors/Managers of Fire Fighting and Prevention Workers	2.083	3.160	1.248
33-2011	Fire Fighters	2.074	2.110	1.474
33-2021	Fire Inspectors and Investigators	2.120	2.773	1.262
33-2022	Forest Fire Inspectors and Prevention Specialists	2.336	2.898	1.298
33-3011	Bailiffs	1.393	1.924	1.350
33-3012	Correctional Officers and Jailers	1.766	1.924	1.398
33-3021	Detectives and Criminal Investigators	1.989	2.557	1.414

33-3031	Fish and Game Wardens	1.750	2.948	1.224
33-3041	Parking Enforcement Workers	1.097	1.624	1.398
33-3051	Police and Sheriff's Patrol Officers	2.062	2.631	1.349
33-3052	Transit and Railroad Police	2.029	2.922	1.324
33-9011	Animal Control Workers	1.474	2.372	1.300
33-9021	Private Detectives and Investigators	2.246	3.024	1.224
33-9032	Security Guards	1.769	1.974	1.248
33-9091	Crossing Guards	2.000	1.672	1.300
33-9092	Lifeguards, Ski Patrol, and Other Recreational Protective Service Workers	1.891	2.248	1.300
35-1011	Chefs and Head Cooks	1.594	2.974	1.050
35-1012	First-Line Supervisors/Managers of Food Preparation and Serving Workers	1.846	2.822	1.024
35-2011	Cooks, Fast Food	1.749	1.346	1.248
35-2012	Cooks, Institution and Cafeteria	1.331	2.296	1.174
35-2014	Cooks, Restaurant	1.600	2.624	1.124
35-2015	Cooks, Short Order	1.874	1.448	1.124
35-2021	Food Preparation Workers	1.451	1.174	1.174
35-3011	Bartenders	1.357	1.846	1.250

35-3021	Combined Food Preparation and Serving Workers, Including Fast Food	1.365	1.174	1.150
35-3022	Counter Attendants, Cafeteria, Food Concession, and Coffee Shop	1.994	1.522	1.300
35-3031	Waiters and Waitresses	1.657	1.572	1.348
35-3041	Food Servers, Nonrestaurant	1.914	1.624	1.300
35-9011	Dining Room and Cafeteria Attendants and Bartender Helpers	1.766	1.372	1.300
35-9021	Dishwashers	1.727	1.046	1.124
35-9031	Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop	2.149	2.122	1.348
37-1011	First-Line Supervisors/Managers of Housekeeping and Janitorial Workers	1.409	2.649	1.087
37-1012	First-Line Supervisors/Managers of Landscaping, Lawn Service, and Groundskeeping Workers	1.383	2.785	1.036
37-2011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	1.746	1.374	1.174
37-2012	Maids and Housekeeping Cleaners	1.223	1.298	1.050
37-2021	Pest Control Workers	1.943	1.722	1.250
37-3011	Landscaping and Groundskeeping Workers	1.686	1.272	0.874

37-3012	Pesticide Handlers, Sprayers, and Applicators, Vegetation	1.143	1.472	1.074
37-3013	Tree Trimmers and Pruners	1.086	1.548	0.998
39-1011	Gaming Supervisors	1.720	2.824	1.174
39-1021	First-Line Supervisors/Managers of Personal Service Workers	1.537	2.798	1.074
39-2011	Animal Trainers	1.071	2.998	0.800
39-2021	Nonfarm Animal Caretakers	1.211	2.024	1.248
39-3011	Gaming Dealers	2.132	1.422	1.248
39-3012	Gaming and Sports Book Writers and Runners	2.132	1.422	1.248
39-3021	Motion Picture Projectionists	1.680	1.748	1.298
39-3031	Ushers, Lobby Attendants, and Ticket Takers	2.240	1.222	1.174
39-3091	Amusement and Recreation Attendants	1.476	1.548	1.174
39-3092	Costume Attendants	1.526	2.848	0.900
39-3093	Locker Room, Coatroom, and Dressing Room Attendants	1.126	1.848	1.098
39-4011	Embalmers	1.329	2.248	1.198
39-4021	Funeral Attendants	2.057	1.600	1.074
39-5011	Barbers	1.046	2.498	0.800
39-5012	Hairdressers, Hairstylists, and Cosmetologists	1.349	2.648	0.848

39-5091	Makeup Artists, Theatrical and Performance	1.383	2.772	0.874
39-5092	Manicurists and Pedicurists	1.850	2.248	0.824
39-6011	Baggage Porters and Bellhops	2.600	1.272	1.200
39-6021	Tour Guides and Escorts	1.406	2.222	1.148
39-6022	Travel Guides	1.463	2.648	1.098
39-6031	Flight Attendants	1.857	1.724	1.524
39-6032	Transportation Attendants, Except Flight Attendants and Baggage Porters	1.486	1.574	1.324
39-9011	Child Care Workers	1.514	2.272	1.050
39-9021	Personal and Home Care Aides	1.337	2.224	1.198
39-9031	Fitness Trainers and Aerobics Instructors	1.389	3.172	1.098
39-9032	Recreation Workers	1.336	2.898	1.248
39-9041	Residential Advisors	1.093	2.646	1.398
41-1011	First-Line Supervisors/Managers of Retail Sales Workers	1.594	3.272	1.174
41-1012	First-Line Supervisors/Managers of Non-Retail Sales Workers	1.594	3.272	1.174
41-2011	Cashiers	2.029	1.374	1.348
41-2021	Counter and Rental Clerks	1.265	1.772	1.348
41-2022	Parts Salespersons	1.504	2.248	1.374

41-2031	Retail Salespersons	1.359	2.322	1.500
41-3011	Advertising Sales Agents	1.566	2.948	1.174
41-3021	Insurance Sales Agents	1.703	2.848	1.324
41-3031	Securities, Commodities, and Financial Services Sales Agents	1.726	3.086	1.124
41-3041	Travel Agents	2.480	2.598	1.148
41-4011	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	1.420	2.873	1.303
41-4012	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	1.603	2.874	1.374
41-9011	Demonstrators and Product Promoters	0.914	1.922	1.098
41-9012	Models	0.943	1.700	0.848
41-9022	Real Estate Sales Agents	1.703	3.022	1.074
41-9031	Sales Engineers	1.760	3.072	1.198
41-9041	Telemarketers	1.109	1.922	1.048
41-9091	Door-To-Door Sales Workers, News and Street Vendors, and Related Workers	1.109	1.922	1.048
43-1011	First-Line Supervisors/Managers of Office and Administrative Support Workers	1.635	3.110	1.350
43-2011	Switchboard Operators, Including Answering Service	2.303	1.548	1.374

43-2021	Telephone Operators	1.353	1.486	1.512
43-3011	Bill and Account Collectors	1.486	2.248	1.324
43-3021	Billing and Posting Clerks and Machine Operators	1.600	1.907	1.383
43-3031	Bookkeeping, Accounting, and Auditing Clerks	1.975	2.372	1.248
43-3051	Payroll and Timekeeping Clerks	2.423	2.046	1.350
43-3061	Procurement Clerks	1.357	1.998	1.324
43-3071	Tellers	1.837	1.798	1.474
43-4011	Brokerage Clerks	1.846	2.122	1.300
43-4021	Correspondence Clerks	1.634	1.898	1.300
43-4031	Court, Municipal, and License Clerks	1.532	1.939	1.383
43-4041	Credit Authorizers, Checkers, and Clerks	1.837	2.010	1.348
43-4051	Customer Service Representatives	1.509	2.086	1.386
43-4061	Eligibility Interviewers, Government Programs	1.837	2.048	1.361
43-4071	File Clerks	2.269	1.522	1.300
43-4081	Hotel, Motel, and Resort Desk Clerks	1.629	1.622	1.448
43-4111	Interviewers, Except Eligibility and Loan	1.246	1.674	1.174
43-4121	Library Assistants, Clerical	1.577	1.922	1.474
43-4131	Loan Interviewers and Clerks	1.642	2.274	1.348
43-4141	New Accounts Clerks	1.686	2.000	1.474
43-4151	Order Clerks	1.371	1.898	1.424

43-4161	Human Resources Assistants, Except Payroll and Timekeeping	1.617	2.048	1.348
43-4171	Receptionists and Information Clerks	1.280	1.948	1.324
43-4181	Reservation and Transportation Ticket Agents and Travel Clerks	1.597	2.111	1.386
43-5011	Cargo and Freight Agents	2.851	1.724	1.474
43-5021	Couriers and Messengers	1.971	1.324	1.150
43-5031	Police, Fire, and Ambulance Dispatchers	2.086	2.124	1.498
43-5032	Dispatchers, Except Police, Fire, and Ambulance	1.457	1.898	1.324
43-5041	Meter Readers, Utilities	1.737	1.272	1.500
43-5051	Postal Service Clerks	1.600	1.274	1.574
43-5052	Postal Service Mail Carriers	2.154	1.224	1.450
43-5061	Production, Planning, and Expediting Clerks	2.023	2.074	1.450
43-5071	Shipping, Receiving, and Traffic Clerks	1.537	1.746	1.300
43-5081	Stock Clerks and Order Fillers	1.644	1.279	1.249
43-5111	Weighers, Measurers, Checkers, and Samplers, Recordkeeping	1.509	1.722	1.374
43-6011	Executive Secretaries and Administrative Assistants	1.691	2.124	1.324
43-6012	Legal Secretaries	1.771	2.022	1.298
43-6013	Medical Secretaries	2.217	1.874	1.298

43-6014	Secretaries, Except Legal, Medical, and Executive	1.576	1.798	1.274
43-9011	Computer Operators	2.394	2.424	1.398
43-9021	Data Entry Keyers	1.863	1.398	1.248
43-9022	Word Processors and Typists	1.595	1.698	1.274
43-9031	Desktop Publishers	2.021	2.472	1.300
43-9041	Insurance Claims and Policy Processing Clerks	1.545	1.749	1.374
43-9051	Mail Clerks and Mail Machine Operators, Except Postal Service	1.900	1.510	1.425
43-9061	Office Clerks, General	1.376	1.998	1.374
43-9071	Office Machine Operators, Except Computer	1.126	1.398	1.398
43-9081	Proofreaders and Copy Markers	1.834	1.972	1.348
43-9111	Statistical Assistants	2.280	2.072	1.200
45-1011	First-Line Supervisors/Managers of Farming, Fishing, and Forestry Workers	1.681	2.848	1.153
45-2011	Agricultural Inspectors	2.417	2.498	1.250
45-2021	Animal Breeders	1.229	2.796	0.824
45-2041	Graders and Sorters, Agricultural Products	2.440	1.948	1.350
45-2091	Agricultural Equipment Operators	1.509	2.298	0.974
45-2092	Farmworkers and Laborers, Crop, Nursery, and Greenhouse	2.235	1.711	1.086

45-2093	Farmworkers, Farm and Ranch Animals	1.269	1.748	0.850
45-3011	Fishers and Related Fishing Workers	1.977	1.998	0.974
45-3021	Hunters and Trappers	1.417	2.424	0.648
45-4011	Forest and Conservation Workers	1.377	2.322	1.150
45-4021	Fallers	1.491	1.948	1.274
45-4022	Logging Equipment Operators	1.457	1.748	1.274
45-4023	Log Graders and Scalers	2.051	2.048	1.250
47-1011	First-Line Supervisors/Managers of Construction Trades and Extraction Workers	1.851	2.986	1.224
47-2011	Boilermakers	2.257	2.500	1.424
47-2021	Brick masons and Block masons	2.263	2.248	1.100
47-2022	Stonemasons	1.371	2.248	1.098
47-2031	Carpenters	1.954	2.294	1.186
47-2041	Carpet Installers	1.377	1.748	1.098
47-2042	Floor Layers, Except Carpet, Wood, and Hard Tiles	1.417	1.748	1.098
47-2043	Floor Sanders and Finishers	1.263	1.222	1.074
47-2044	Tile and Marble Setters	1.507	2.098	1.174
47-2051	Cement Masons and Concrete Finishers	1.434	2.098	1.174
47-2053	Terrazzo Workers and Finishers	1.434	2.098	1.174
47-2061	Construction Laborers	1.611	1.422	1.200

47-2071	Paving, Surfacing, and Tamping Equipment Operators	1.514	1.448	1.248
47-2072	Pile-Driver Operators	1.450	1.148	1.100
47-2073	Operating Engineers and Other Construction Equipment Operators	1.480	1.760	1.224
47-2081	Drywall and Ceiling Tile Installers	1.741	2.010	1.261
47-2082	Tapers	1.186	1.772	1.250
47-2111	Electricians	1.777	2.774	1.050
47-2121	Glaziers	1.566	1.774	0.974
47-2131	Insulation Workers, Floor, Ceiling, and Wall	1.526	1.622	1.150
47-2132	Insulation Workers, Mechanical	1.526	1.622	1.150
47-2141	Painters, Construction and Maintenance	1.469	1.974	1.148
47-2142	Paperhangers	1.491	1.900	1.148
47-2151	Pipelayers	2.006	1.548	1.174
47-2152	Plumbers, Pipefitters, and Steamfitters	1.898	2.215	1.125
47-2161	Plasterers and Stucco Masons	1.886	2.174	1.174
47-2171	Reinforcing Iron and Rebar Workers	1.571	1.948	1.200
47-2181	Roofers	1.457	1.798	1.000
47-2211	Sheet Metal Workers	1.703	2.174	1.324
47-2221	Structural Iron and Steel Workers	1.798	1.648	1.250

47-3011	Helpers--Brickmasons, Blockmasons, Stonemasons, and Tile and Marble Setters	2.549	1.398	1.224
47-3012	Helpers--Carpenters	2.117	1.248	1.224
47-3013	Helpers--Electricians	2.017	1.422	1.374
47-3014	Helpers--Painters, Paperhangers, Plasterers, and Stucco Masons	1.320	1.222	1.274
47-3015	Helpers--Pipelayers, Plumbers, Pipefitters, and Steamfitters	2.577	1.348	1.298
47-4011	Construction and Building Inspectors	1.857	2.598	1.274
47-4021	Elevator Installers and Repairers	2.007	2.374	1.274
47-4031	Fence Erectors	1.271	1.572	1.124
47-4041	Hazardous Materials Removal Workers	2.560	1.498	1.398
47-4051	Highway Maintenance Workers	1.589	1.448	1.224
47-4061	Rail-Track Laying and Maintenance Equipment Operators	2.500	1.422	1.324
47-4071	Septic Tank Servicers and Sewer Pipe Cleaners	1.257	1.722	1.174
47-5011	Derrick Operators, Oil and Gas	1.986	1.450	1.298
47-5012	Rotary Drill Operators, Oil and Gas	2.243	1.896	1.274
47-5013	Service Unit Operators, Oil, Gas, and Mining	1.607	2.446	1.398
47-5021	Earth Drillers, Except Oil and Gas	1.608	1.648	1.174

47-5031	Explosives Workers, Ordnance Handling Experts, and Blasters	2.274	2.050	1.274
47-5041	Continuous Mining Machine Operators	1.936	1.348	1.350
47-5042	Mine Cutting and Channeling Machine Operators	2.557	1.772	1.348
47-5051	Rock Splitters, Quarry	2.450	1.398	1.074
47-5061	Roof Bolters, Mining	2.606	1.496	1.300
47-5071	Roustabouts, Oil and Gas	1.521	1.548	1.298
47-5081	Helpers--Extraction Workers	1.560	1.372	1.374
49-1011	First-Line Supervisors/Managers of Mechanics, Installers, and Repairers	2.257	2.974	1.224
49-2011	Computer, Automated Teller, and Office Machine Repairers	1.726	2.173	1.340
49-2021	Radio Mechanics	1.514	2.424	1.274
49-2022	Telecommunications Equipment Installers and Repairers, Except Line Installers	1.882	2.253	1.434
49-2091	Avionics Technicians	3.097	2.524	1.424
49-2092	Electric Motor, Power Tool, and Related Repairers	1.755	2.290	1.324
49-2093	Electrical and Electronics Installers and Repairers, Transportation Equipment	2.263	2.422	1.374

49-2094	Electrical and Electronics Repairers, Commercial and Industrial Equipment	2.034	2.824	1.374
49-2095	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay	2.149	2.550	1.324
49-2096	Electronic Equipment Installers and Repairers, Motor Vehicles	2.263	2.422	1.374
49-2097	Electronic Home Entertainment Equipment Installers and Repairers	1.634	2.448	1.300
49-3011	Aircraft Mechanics and Service Technicians	2.432	2.282	1.265
49-3021	Automotive Body and Related Repairers	1.760	2.324	1.174
49-3022	Automotive Glass Installers and Repairers	1.537	2.172	1.198
49-3023	Automotive Service Technicians and Mechanics	1.919	2.511	1.000
49-3031	Bus and Truck Mechanics and Diesel Engine Specialists	2.303	2.348	1.124
49-3041	Farm Equipment Mechanics	1.571	2.400	1.074
49-3042	Mobile Heavy Equipment Mechanics, Except Engines	1.691	2.448	1.174
49-3043	Rail Car Repairers	1.671	2.398	1.248
49-3051	Motorboat Mechanics	2.194	2.348	1.148
49-3052	Motorcycle Mechanics	1.429	2.324	1.124

49-3053	Outdoor Power Equipment and Other Small Engine Mechanics	1.429	2.324	1.124
49-3091	Bicycle Repairers	1.293	2.498	1.100
49-3092	Recreational Vehicle Service Technicians	1.486	2.272	1.300
49-3093	Tire Repairers and Changers	1.457	2.098	1.248
49-9011	Mechanical Door Repairers	2.223	2.198	1.324
49-9012	Control and Valve Installers and Repairers, Except Mechanical Door	2.318	2.189	1.340
49-9021	Heating, Air Conditioning, and Refrigeration Mechanics and Installers	2.340	2.522	1.312
49-9031	Home Appliance Repairers	1.514	2.210	1.237
49-9041	Industrial Machinery Mechanics	1.819	2.198	1.224
49-9042	Maintenance and Repair Workers, General	1.703	2.296	1.324
49-9043	Maintenance Workers, Machinery	1.486	2.198	1.300
49-9044	Millwrights	1.771	2.246	1.300
49-9045	Refractory Materials Repairers, Except Brickmasons	1.543	2.224	1.224
49-9051	Electrical Power-Line Installers and Repairers	2.543	2.324	1.474
49-9052	Telecommunications Line Installers and Repairers	1.497	2.098	1.450
49-9061	Camera and Photographic Equipment Repairers	1.371	2.624	1.150
49-9062	Medical Equipment Repairers	1.843	2.524	1.298

49-9063	Musical Instrument Repairers and Tuners	1.666	2.542	1.193
49-9064	Watch Repairers	1.766	2.648	1.100
49-9091	Coin, Vending, and Amusement Machine Servicers and Repairers	1.429	2.200	1.224
49-9092	Commercial Divers	1.874	2.550	1.098
49-9093	Fabric Menders, Except Garment	2.040	1.846	1.274
49-9094	Locksmiths and Safe Repairers	2.183	2.398	1.248
49-9095	Manufactured Building and Mobile Home Installers	1.486	2.272	1.300
49-9096	Riggers	1.846	2.422	1.348
49-9097	Signal and Track Switch Repairers	1.850	2.324	1.450
49-9098	Helpers--Installation, Maintenance, and Repair Workers	2.074	1.274	1.274
51-1011	First-Line Supervisors/Managers of Production and Operating Workers	1.697	2.972	1.224
51-2011	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	2.116	1.990	1.333
51-2021	Coil Winders, Tapers, and Finishers	2.057	1.650	1.348
51-2022	Electrical and Electronic Equipment Assemblers	1.703	2.174	1.274
51-2023	Electromechanical Equipment Assemblers	2.206	1.798	1.324
51-2031	Engine and Other Machine Assemblers	2.680	1.998	1.324

51-2041	Structural Metal Fabricators and Fitters	2.004	2.011	1.362
51-2093	Timing Device Assemblers, Adjusters, and Calibrators	1.726	2.322	1.098
51-3011	Bakers	1.697	2.022	1.287
51-3021	Butchers and Meat Cutters	1.263	2.048	1.124
51-3022	Meat, Poultry, and Fish Cutters and Trimmers	1.351	1.198	1.198
51-3023	Slaughterers and Meat Packers	1.317	1.698	1.100
51-3091	Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders	2.354	1.574	1.274
51-3092	Food Batchmakers	2.107	1.924	1.374
51-3093	Food Cooking Machine Operators and Tenders	1.583	1.598	1.298
51-4011	Computer-Controlled Machine Tool Operators, Metal and Plastic	1.646	1.674	1.374
51-4012	Numerical Tool and Process Control Programmers	1.811	2.824	1.348
51-4021	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	2.223	1.772	1.398
51-4022	Forging Machine Setters, Operators, and Tenders, Metal and Plastic	1.634	1.900	1.374
51-4023	Rolling Machine Setters, Operators, and Tenders, Metal and Plastic	1.846	2.048	1.450

51-4031	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	1.677	1.792	1.412
51-4032	Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic	2.194	1.822	1.450
51-4033	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic	1.529	1.786	1.386
51-4034	Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic	1.851	1.874	1.450
51-4035	Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic	1.594	1.924	1.424
51-4041	Machinists	1.794	2.572	1.350
51-4051	Metal-Refining Furnace Operators and Tenders	1.474	1.624	1.348
51-4052	Pourers and Casters, Metal	1.514	1.424	1.274
51-4061	Model Makers, Metal and Plastic	2.257	2.622	1.300
51-4062	Patternmakers, Metal and Plastic	1.663	2.374	1.274
51-4071	Foundry Mold and Coremakers	1.886	1.874	1.374
51-4072	Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic	1.592	1.643	1.339
51-4081	Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic	1.546	1.697	1.325

51-4111	Tool and Die Makers	2.343	2.324	1.250
51-4121	Welders, Cutters, Solderers and Brazers	2.169	1.728	1.239
51-4122	Welding, Soldering, and Brazing Machine Setters, Operators, and Tenders	1.800	1.636	1.312
51-4191	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic	1.488	1.698	1.399
51-4192	Lay-Out Workers, Metal and Plastic	1.657	2.374	1.274
51-4193	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic	1.713	1.605	1.400
51-4194	Tool Grinders, Filers, and Sharpeners	2.126	2.098	1.274
51-5011	Bindery Workers	2.111	1.849	1.348
51-5012	Bookbinders	1.993	2.274	1.450
51-5021	Job Printers	2.250	2.174	1.200
51-5022	Prepress Technicians and Workers	1.846	2.209	1.264
51-5023	Printing Machine Operators	1.900	1.895	1.332
51-6011	Laundry and Dry-Cleaning Workers	1.561	1.840	1.274
51-6021	Pressers, Textile, Garment, and Related Materials	1.546	1.532	1.207
51-6031	Sewing Machine Operators	1.774	1.786	1.374
51-6041	Shoe and Leather Workers and Repairers	1.389	2.498	0.998
51-6042	Shoe Machine Operators and Tenders	1.383	1.774	1.300

51-6051	Sewers, Hand	1.480	1.774	1.074
51-6052	Tailors, Dressmakers, and Custom Sewers	1.649	2.785	0.899
51-6061	Textile Bleaching and Dyeing Machine Operators and Tenders	1.583	1.924	1.398
51-6062	Textile Cutting Machine Setters, Operators, and Tenders	1.663	1.672	1.398
51-6063	Textile Knitting and Weaving Machine Setters, Operators, and Tenders	1.663	1.672	1.398
51-6064	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders	1.663	1.672	1.398
51-6091	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers	2.097	1.674	1.398
51-6092	Fabric and Apparel Patternmakers	1.606	2.298	1.174
51-6093	Upholsterers	1.743	2.524	0.974
51-7011	Cabinetmakers and Bench Carpenters	1.480	2.322	1.174
51-7021	Furniture Finishers	1.257	2.348	1.074
51-7031	Model Makers, Wood	1.629	2.348	1.174
51-7032	Patternmakers, Wood	1.629	2.348	1.174
51-7041	Sawing Machine Setters, Operators, and Tenders, Wood	1.852	1.611	1.311

51-7042	Woodworking Machine Setters, Operators, and Tenders, Except Sawing	1.946	1.798	1.324
51-8011	Nuclear Power Reactor Operators	1.983	1.948	1.548
51-8012	Power Distributors and Dispatchers	1.806	2.248	1.424
51-8013	Power Plant Operators	1.680	1.636	1.411
51-8021	Stationary Engineers and Boiler Operators	1.809	1.799	1.299
51-8031	Water and Liquid Waste Treatment Plant and System Operators	2.149	2.150	1.298
51-8091	Chemical Plant and System Operators	2.423	2.272	1.398
51-8092	Gas Plant Operators	2.243	2.098	1.412
51-8093	Petroleum Pump System Operators, Refinery Operators, and Gaugers	2.182	1.933	1.416
51-9011	Chemical Equipment Operators and Tenders	1.809	1.899	1.362
51-9012	Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders	1.623	1.924	1.374
51-9021	Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders	1.240	1.898	1.350
51-9022	Grinding and Polishing Workers, Hand	1.349	1.622	1.250
51-9023	Mixing and Blending Machine Setters, Operators, and Tenders	1.240	1.898	1.350

51-9031	Cutters and Trimmers, Hand	2.263	1.522	1.124
51-9032	Cutting and Slicing Machine Setters, Operators, and Tenders	1.610	1.786	1.312
51-9041	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	1.631	1.811	1.350
51-9051	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders	2.240	1.598	1.298
51-9061	Inspectors, Testers, Sorters, Samplers, and Weighers	1.873	2.504	1.348
51-9071	Jewelers and Precious Stone and Metal Workers	1.904	2.682	1.011
51-9081	Dental Laboratory Technicians	1.771	2.272	1.348
51-9082	Medical Appliance Technicians	2.177	2.498	1.324
51-9083	Ophthalmic Laboratory Technicians	2.054	2.222	1.312
51-9111	Packaging and Filling Machine Operators and Tenders	2.029	1.750	1.350
51-9121	Coating, Painting, and Spraying Machine Setters, Operators, and Tenders	1.360	1.736	1.350
51-9122	Painters, Transportation Equipment	1.663	1.924	1.324
51-9123	Painting, Coating, and Decorating Workers	2.194	1.998	1.224
51-9131	Photographic Process Workers	1.741	2.161	1.217
51-9132	Photographic Processing Machine Operators	2.097	1.898	1.324
51-9141	Semiconductor Processors	1.714	1.924	1.300

51-9191	Cementing and Gluing Machine Operators and Tenders	2.000	1.748	1.374
51-9192	Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders	1.357	1.748	1.324
51-9193	Cooling and Freezing Equipment Operators and Tenders	1.623	1.650	1.298
51-9194	Etchers and Engravers	1.870	2.176	1.161
51-9195	Molders, Shapers, and Casters, Except Metal and Plastic	1.740	2.109	1.170
51-9196	Paper Goods Machine Setters, Operators, and Tenders	1.543	1.696	1.348
51-9197	Tire Builders	2.036	1.600	1.324
51-9198	Helpers--Production Workers	1.411	1.312	1.236
53-1021	First-Line Supervisors/Managers of Helpers, Laborers, and Material Movers, Hand	2.200	2.872	1.198
53-1031	First-Line Supervisors/Managers of Transportation and Material-Moving Machine and Vehicle Operators	1.691	2.998	1.198
53-2011	Airline Pilots, Copilots, and Flight Engineers	2.251	2.748	1.250
53-2012	Commercial Pilots	2.251	2.748	1.250
53-2021	Air Traffic Controllers	2.303	2.574	1.524
53-3011	Ambulance Drivers and Attendants, Except Emergency Medical Technicians	2.686	1.698	1.298

53-3021	Bus Drivers, Transit and Intercity	1.937	1.848	1.848
53-3022	Bus Drivers, School	1.669	1.800	1.724
53-3031	Driver/Sales Workers	1.320	2.124	1.224
53-3032	Truck Drivers, Heavy and Tractor-Trailer	1.889	2.049	1.236
53-3033	Truck Drivers, Light or Delivery Services	2.471	1.924	1.250
53-3041	Taxi Drivers and Chauffeurs	1.571	1.922	1.074
53-4011	Locomotive Engineers	2.443	2.100	1.574
53-4012	Locomotive Firers	2.143	1.672	1.474
53-4013	Rail Yard Engineers, Dinkey Operators, and Hostlers	1.634	1.772	1.524
53-4021	Railroad Brake, Signal, and Switch Operators	2.229	1.523	1.473
53-4031	Railroad Conductors and Yardmasters	1.789	2.646	1.524
53-4041	Subway and Streetcar Operators	2.531	1.574	1.598
53-5011	Sailors and Marine Oilers	1.650	1.811	1.324
53-5021	Captains, Mates, and Pilots of Water Vessels	2.097	2.965	1.117
53-5022	Motorboat Operators	2.214	2.498	1.124
53-5031	Ship Engineers	1.697	2.898	1.224
53-6011	Bridge and Lock Tenders	1.871	2.098	1.224
53-6021	Parking Lot Attendants	1.320	1.424	1.050
53-6031	Service Station Attendants	1.434	1.748	1.150
53-6041	Traffic Technicians	2.164	2.148	1.300

53-6051	Transportation Inspectors	1.992	2.395	1.370
53-7011	Conveyor Operators and Tenders	1.543	1.748	1.474
53-7021	Crane and Tower Operators	2.377	1.848	1.324
53-7031	Dredge Operators	1.507	1.648	1.224
53-7032	Excavating and Loading Machine and Dragline Operators	1.710	1.799	1.225
53-7033	Loading Machine Operators, Underground Mining	1.521	1.498	1.398
53-7041	Hoist and Winch Operators	1.531	1.622	1.248
53-7051	Industrial Truck and Tractor Operators	1.697	1.874	1.398
53-7061	Cleaners of Vehicles and Equipment	2.566	1.296	1.148
53-7062	Laborers and Freight, Stock, and Material Movers, Hand	1.515	1.523	1.299
53-7063	Machine Feeders and Offbearers	1.863	1.372	1.274
53-7064	Packers and Packagers, Hand	1.349	1.248	1.300
53-7071	Gas Compressor and Gas Pumping Station Operators	1.983	1.623	1.299
53-7072	Pump Operators, Except Wellhead Pumpers	1.497	1.748	1.474
53-7073	Wellhead Pumpers	1.474	1.600	1.374
53-7081	Refuse and Recyclable Material Collectors	0.954	1.148	1.374
53-7111	Shuttle Car Operators	1.436	1.398	1.424