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The Influence of Labor and Employment Conditions on Worker's Health in the United States

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Abstract

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State labor laws and working conditions have important implications for worker's health and well-being. Recently, a rise in precarious employment and state preemption laws—legislation that restricts the power of lower-level jurisdictions—has stymied local attempts to meet the needs of localities and enact labor laws and protections that exceed federal minimums (Scharff, 2017; Riverstone-Newell, 2017). Scholars argue that these recent state preemption efforts jeopardize public health and negatively impact workers' health and well-being (Pomeranz & Pertschuk, 2017). While the health effects of generous labor laws are well documented (e.g., Leigh et al., 2019; Isaacs, Healy & Peters, 2017), less is known about the link between state labor preemption laws and workers' health despite calls to quantify these purported consequences across different policy domains and population health outcomes (Carr et al., 2020). To fill this gap, I use an equity-first lens to first examine whether variations in and dimensions of

four US state labor preemption laws are associated with adverse mental health outcomes for workers and whether outcomes are patterned by gender, income, race/ethnicity, and education (Paper 1). Second, I investigate whether variations in and dimensions of state labor preemption are associated with health care access for US workers with a high school education or less, and whether outcomes vary by gender, race/ethnicity, and insurance coverage (Paper 2). Finally, I assess whether nonstandard or irregular work schedules, a potential consequence of preempted fair scheduling laws, are getting 'under the skin' of workers at young adulthood and early mid-life using biomarkers of cardiovascular health (CVH). I also examine whether CVH outcomes vary by gender, race/ethnicity, education, or employment in the service industry (Paper 3). To address these questions, I employ a series of bivariate, linear, and logistic regression models using two nationally representative health datasets (Add Health and the Behavioral Risk Factor Surveillance System Survey) and state-level preemption law measures (Economic Policy Institute, 2019). In paper 1, findings suggest female workers that lived in states with multiple preempted labor laws, particularly states that restricted temporal-based preemption laws like fair scheduling ordinances, were at significantly higher odds of reporting poor mental health, and this association was pronounced for low income and Hispanic females. Notably, state preemption had no significant effect on poor mental health outcomes for male workers suggesting that the mental health consequences of state preemption disproportionately impacts females. In paper 2, results show female workers with a high school education or less that lived in states with multiple types and instances of preempted labor laws were at significantly higher odds of reporting cost-related barriers to health care regardless of their health insurance status, and this association was pronounced for Black and white female workers. Black male workers were also at significantly higher odds of experiencing barriers to health care in states with multiple preemption laws.

Findings support evidence that racial inequities in health may be exacerbated by state preemption. Finally, findings from paper 3 indicate workers subjected to nonstandard work schedules in young adulthood were at increased risk of obesity and high inflammation during early mid-life and as a result may be at increased risk of cardiovascular disease. Of note, the health consequences of nonstandard work schedules appeared to disproportionately affect cardiovascular health outcomes for female and Black workers as well as workers employed outside of the service industry. Findings from this dissertation have important implications for social justice, labor policy, and health equity.

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Chapter 1

ACKNOWLEDGEMENTS

First, I would like to thank my dissertation chair and amazing mentor, Melissa Martinson, for being a guiding force from the very beginning of my time at UW and offering support every step along the way. I would also like to thank my committee members—David Takeuchi, Jennie Romich, and Jerry Herting—who have provided invaluable feedback not only for this dissertation but my qualifying paper as well. I'd also like to acknowledge the training, mentorship, and technical support I received from the Institute for Translational Health Sciences, the Center for Statistics and the Social Sciences, the Center for Studies in Demography and Ecology, and the UW Data Collaborative as well as the financial support I received from the Horowitz Foundation for Social Policy, the Magnuson Scholarship, and the Almgren Dissertation Award, without which the completion of this dissertation would not be possible.

PROJECT INTRODUCTION

Since the 1970s, the United States (US) labor market has undergone significant shifts due in part to declines in labor unions, market regulation, and the welfare state as well as a rise in flexible employment and globalization (Benach et al., 2014; Scott, 2004). As a result, workers have experienced stagnant incomes and wages, declines in employer benefits, and increases in low-quality, precarious employment conditions (Benach et al., 2014; Howell & Kalleberg, 2019). These shifts are associated with widening socioeconomic disparities in health and well-being (Benach et al., 2014; Leigh & De Vogli, 2016; Pickett & Wilkinson, 2015) and felt most severely among low-income workers, retail and service workers, females, and workers of color who are disproportionately subject to precarious labor conditions (Bernhardt et al., 2009).

State and local governments have attempted to counter these inequities by putting forth various labor protections and wage standards that exceed federal minimums such as increasing minimum wages, establishing paid family and sick leave mandates, offering prevailing wage protections, and improving schedule stability through fair scheduling laws. While these policies are designed to protect worker's rights in economic and temporal ways, several studies have shown that they may also have important implications for improving worker's health and well-being (e.g., Leigh et al., 2019) as outlined below.

Minimum wage laws ensure workers are sufficiently compensated to meet their basic economic needs and participate in civic and leisure activities (Fairris & Reich, 2005). Under the federal minimum wage law, employers must pay covered nonexempt workers at or above the federal minimum wage which was set at $7.25 per hour as of July 2009 (US Bureau of Labor Statistics, 2020). Currently, thirty states and Washington D.C. have minimum wages above the federal minimum (US Department of Labor, 2021). According to the Bureau of Labor Statistics, 1.6 million US workers made wages at or below the federal minimum wage in 2019 and the highest percentages of minimum wage workers were clustered in the south (US Bureau of Labor Statistics, 2020). Moreover, in 2019 females were more likely to hold minimum wage jobs as compared to men and approximately 60% of minimum wage workers were employed in service industry jobs (US Bureau of Labor Statistics, 2020). Several studies have examined the health effects of minimum wage increases with mixed results (e.g., Leigh, Leigh, & Du, 2019). For instance, some studies have found increases in state minimum wages were associated with improved infant health outcomes including decreases in low birth weight and postneonatal mortality (Komro et al., 2016), reductions in heart disease deaths (Van Dykea et al., 2018), decreases in functional limitations (Andreyeva & Ukert, 2018), improvements in self rated health for non-White groups and women (Andreyeva & Ukert, 2018), and decreases in suicide (Dow et al., 2020). Other research suggests that increases in state minimum wages lead to poor self-rated health for men (Horn et al., 2017), obesity (Buszkiewicz et al., 2021; Andreyeva & Ukert, 2018), an elevated BMI (Buszkiewicz et al., 2021), and decreases in fruit and vegetable consumption (Andreyeva & Ukert, 2018).

Paid leave laws provide workers with paid time off from work, including vacations, holidays, family, personal and sick leave (Siqueira et al., 2014). While the federal Family and Medical Leave Act of 1993 (FMLA) provides covered workers with unpaid leave for certain family and medical needs, currently there is no federal paid leave mandate in place in the US. As a result, some employers and localities have adopted their own policies. As of 2021, nine states have enacted paid family leave laws and 16 states have established paid sick leave laws. In 2019, individuals in the construction and service industry made up the smallest percentage of workers with access to paid sick leave benefits (56% and 58% respectively) (US Bureau of Labor Statistics, 2020) and undocumented, part-time, and low wage workers were least likely to receive paid leave benefits from their employers (Ponce et al., 2008). Evidence shows paid leave laws are consistently linked to positive health outcomes (Isaacs, Healy & Peters, 2017). For instance, state adopted paid family leave laws are associated with improvements in infant and child health outcomes including decreases in infant and mother rehospitalizations (Jou et al., 2018), longer duration of breastfeeding (Huang & Yang 2015; Appelbaum & Milkman, 2011), as well as reductions in neonatal and child mortality, low birth weight, and premature birth (Stearns, 2015; Rossin, 2011). The benefits of paid family leave appear to be especially impactful for unmarried mothers and Black mothers (Stearns, 2015). In addition, research shows paid sick leave mandates may reduce influenza-like illness transmission and mortality rates (Pichler et al., 2021), and increase in the likelihood of health care utilization (Peipins et al., 2021; DeRigne et al., 2017).

Prevailing wage laws require public works projects to set wage and benefit rates at levels equivalent to those prevailing for similar jobs in the local market. While there is evidence to suggest prevailing wages improve workers' income, wages, and benefits such as health insurance coverage and pension plans (Monzo & Duncan, 2018) as well as reduce injury rates (Dickson et al., 2013), the literature on prevailing wages and health is extremely limited.

Fair scheduling laws require employers to provide workers with stable, predictable, and flexible work schedules including advanced notice of work hours or compensation for last-minute schedule changes (Economic Policy Institute, 2019). Currently, two states and eight localities have passed fair scheduling laws. The literature on fair scheduling practices and worker health is limited. One study found that Seattle, Washington's Secure Scheduling ordinance (i.e. fair scheduling law) improved workers' subjective well-being, sleep quality, and economic security (Harknett et al., 2021). Another study found that Emeryville California's Fair Workweek Ordinance was associated with improvements in parental well-being and declines in sleep difficulty among low wage workers with families (Ananat, Glassman-Pines & Fitz-Henley, 2022).

Despite the robust body of empirical and conceptual evidence documenting the positive association between various state labor laws and workers' health and well-being, a new wave of state preemption laws has threatened to dismantle these efforts and hamper the ability of municipalities to address local labor inequities and the distribution of social determinants of health (Carr et al., 2020; Institute of Medicine, 2011). Preemption, which allows a higher level of government to preempt, or restrict, the authority of a lower level of government when the two authorities come into conflict about a particular issue, was historically used as a tool to legally block discriminatory state and local laws (Carr et al., 2020; McGowan et al., 2016). However, in the last decade a surge of 'hyper' preemptive action has spread across the US (Scharff, 2017), often at the encouragement of particular industries (Pomeranz & Pertschuk, 2017; Gorovitz, Mosher & Pertschuk, 1998) or when state authorities oppose local legislative agendas (Montez et al., 2020; Riverstone-Newell, 2017). As a result, recent preemption efforts have blocked several local ordinances and bills including nutrition labeling in restaurants, hydraulic fracking bans, anti-discrimination efforts, and labor and employment efforts including minimum wage increases, paid sick leave, prevailing wage and fair scheduling standards (Von Wilpert, 2017; Riverstone-Newell, 2017). Scholars and public health professionals contend hyper preemption exacerbates health inequities and poses a significant threat to public health (Carr et al., 2020; Pomeranz & Pertschuk, 2017; Institute of Medicine, 2011).

Emerging evidence supports these claims. For instance, Montez (2018) found declines in life expectancy were linked to increases in broad preemption use. Wolf and colleagues (2021) found state minimum wage preemption may have contributed to infant deaths (Wolf, Monnat & Montez, 2021), and Melton-Fant (2020) found that inclusionary zoning preemption was associated with delayed medical care and poor self-rated health, particularly for Black adults.

While evidence of preemption's deleterious effects is growing, a gap remains in our understanding of how different instances and forms of preemption within specific policy areas is impacting population health and well-being across places and populations. As such, this dissertation sought to understand whether state preemption of four commonly preempted state labor laws (minimum wage, paid leave, prevailing wage, and fair scheduling) was associated with mental health consequences and cost-related barriers to health care for workers across the US. I also assessed whether nonstandard or irregular work schedules, a potential consequence of state preempted fair scheduling laws, impacted cardiovascular health (CVH) outcomes for workers in young adulthood and early mid-life. The first two papers of this dissertation utilized data from the Behavioral Risk Factor Surveillance System Survey (BRFSS) merged with state-level preemption law measures (Economic Policy Institute, 2019) to examine whether variations in the number and types of state labor preemption laws enacted shaped mental health and health care access outcomes. The final paper of this dissertation used public and restricted biomarker data from the National Longitudinal Study of Adolescent to Adult Health (Add Health) to conduct a cross-sectional analysis of nonstandard and irregular work hours and poor CVH outcomes for workers at young adulthood as well as a longitudinal analysis of work schedules at young adulthood and poor CVH outcomes at early mid-life.

Building on recent calls to examine the health effects of structural inequalities like state preemption, this research has several implications for social justice, labor policy and health equity. First, findings from this study will expand on current research efforts by quantifying the association between state policy contexts and workers' health and well-being and provide important insights into how preemption may disproportionately shape health inequities by place and across populations. Additionally, findings lend insight into how policy structures and institutional actors create and perpetuate discriminatory systems that worsen health inequities. Importantly, this work moves beyond values-informed research to elucidate the structures and upstream factors that shape health inequities to better inform how we might address such systemic inequalities by advancing a 'health in all policies' agenda for promoting equity (Miller et al., 2017).

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CHAPTER 1

STATE PREEMPTION OF FOUR LABOR LAWS AND THE MENTAL HEALTH OF US WORKERS AGED 18-64

Abstract

This study examined whether state preemption of four labor laws which include minimum wage, prevailing wage, paid leave, and fair scheduling ordinances were associated with poor mental health for US workers aged 18-64. I also assessed whether mental health outcomes differed by economic or temporal dimensions of state labor preemption and explored potential variation in mental health outcomes by worker's gender, income, race/ethnicity, and education. Using 2019 data from the Behavioral Risk Factor Surveillance System (BRFSS) Survey (Centers for Disease Control and Prevention, 2019) merged with state-level preemption law measures (Economic Policy Institute, 2019), I employed a series of weighted bivariate and multivariate logistic regression models to examine whether the number of state preemption laws or the type of state preemption laws enacted were associated with adverse mental health outcomes. Findings indicate female workers that lived in states that enacted multiple preemptive labor laws were at significantly higher odds of reporting poor mental health as compared with female workers who lived in states with no preemption. This relationship was pronounced for Hispanic females. When considering whether the effects of economic or temporal forms of state labor preemption exacerbated poor mental health, I found state preemption of temporal-based preemption laws such as fair scheduling ordinances significantly increased the likelihood of poor mental health for female workers, and low income and Hispanic females in particular. Notably, I found no statistically significant associations between any amount or type of state preemption and poor mental health for male workers, suggesting that the mental health consequences of state

preemption disproportionately impact female workers. This study considered the influence of state policy contexts on population health and provides new insights about the association between state labor preemption laws and mental health outcomes for workers across the US. Findings support growing concerns that increases in state preemption may have significant consequences for population health (Carr et al., 2020; Crosbie & Schmidt, 2020; Montez, 2020; Pomeranz & Pertschuk, 2017; Wolf et al., 2021) and offers important implications for policymakers to advance a ‘health in all policies’ approach for promoting equity.

Introduction

The social, economic, and political conditions in which people live and work shape health and mental health in powerful ways (Braveman & Gottlieb, 2014; World Health Organization, 2008). The inequitable distribution of these social conditions, commonly referred to as social determinants of health (SDOH), across groups and places contributes to persistent health and mental health inequities (Alegria et al., 2019; Satcher, 2010; Lahelma et al., 2006; Zimmerman & Katon, 2005). Academics and policymakers recognize that various state and local policies play an important role in the distribution of SDOH to address health and mental health inequities (Leigh, Leigh & Du, 2019).

Recently, scholars have acknowledged the rise in state preemption laws—the process by which state governments restrict the legislative authority of lower-level governments—and its potential to advance or undermine local efforts to adequately distribute SDOH (Carr et al., 2020; Pomeranz & Pertschuk, 2017; Riverstone-Newell, 2017). On the one hand, preemptive state actions used to create expansive and robust state-wide protections when local authorities enact harmful policies is decidedly essential, yet hyper, or misused, state preemption that threatens the ability of municipalities to address local needs and innovatively distribute social determinants of health may have serious health and mental health consequences (Carr et al., 2020). The National Academy of Medicine has called upon state legislators to eliminate preemptive legislation that has the potential to hinder health and well-being (Institute of Medicine, 2011), which left unchecked, poses a significant threat to public health (Carr et al., 2020; Pomeranz & Pertschuk, 2017).

Emerging research supports these concerns. Broad state preemption is associated with declines in life expectancy (Montez, 2018), and state preemption of minimum wage laws may have contributed to increases in infant mortality rates (Wolf, Monnat & Montez, 2021). Melton-Fant (2020) examined the relationship between state preemption of inclusionary zoning policies, delayed medical care and self-rated health among different demographic groups and found state preemption of inclusionary zoning policies was associated with adverse health outcomes, particularly for Black adults who had the highest probability of reporting poor or fair self-rated health status.

Although recent preemptive actions have been framed as health harming, history shows preemption is not inherently negative (Briffault, 2018). More research is needed utilizing an equity-first lens to investigate the impacts of preemption on various health outcomes and inequities (Carr et al., 2020), particularly mental health outcomes which remain understudied in the literature. Undertaking a nuanced analysis of preemption's mental health effects is critical for the advancement of health equity (Carr et al., 2020). This study attempts to fill these gaps by examining the relationship between state preemption of four labor laws including minimum wage, prevailing wage, paid leave and fair scheduling ordinances and the mental health of workers across the United States (US) using an equity-first framework (Carr et al., 2020).

Background

Under the Supremacy Clause of the US Constitution, a higher level of government can preempt, or restrict, the authority of a lower level of government when the two authorities come into conflict about a particular issue. As such, state authorities have the power to preempt local jurisdictions just as the federal government can restrict the authority of state governments to regulate a particular issue. Historically, preemption was used by industry groups as a tool to comply with one governing body (state or federal) as opposed to numerous local jurisdictions (Riverstone-Newell, 2017). During the civil rights era, the federal government used preemption to block discriminatory state and local laws resulting in more equitable systems and public health protections (Carr et al., 2020; McGowan et al., 2016).

In recent years, however, use of preemption has shifted from a negotiating tool to a suppression tactic designed to weaken protections and halt progress often at the encouragement of particular industries (Pomeranz & Pertschuk, 2017; Gorovitz, Mosher & Pertschuk, 1998) and state authorities that are unsupportive of local legislative agendas (Montez et al., 2020; Riverstone-Newell, 2017). Scholars have conceptualized this new wave of legislative action as 'hyper preemption' (Scharff, 2017) due to the dramatic increase in the number and variety of preemptive bills sanctioned by states across the US within the housing, public health, environmental, economic, labor and employment sectors (Riverstone-Newell, 2017).

Notably, the rise in state preemption of local labor and wage laws has been particularly severe (von Wilpert, 2017). What was once historically used to establish statewide wage and labor standards that restricted local governments from enacting labor ordinances that fell below state standards has, in recent years, become an effort to suppress the political power of localities (Montez et al., 2020; Riverstone-Newell, 2017). As of 2019, thirty state legislatures have imposed various labor preemption laws curtailing local attempts to provide minimum wage increases, paid sick leave, prevailing wage, and fair scheduling standards (Von Wilpert, 2017). State efforts to restrict local municipalities from enacting more equitable labor standards disproportionately impact people of color, women, and low-income workers (Blair et al., 2020).

Conceptual Framework

State Labor Policy Contexts as Fundamental Causes of Worker's Mental Health

SDOH frameworks have evolved to consider the ways in which upstream factors shape downstream determinants that impact mental health outcomes and access to services (Allen et al., 2014). Fundamental cause theory (FCT) provides one such theoretical framework for understanding how structural conditions, such as state policy contexts, fundamentally shape mental health. FCT is based on the premise that social conditions fundamentally cause health inequities that persist over time, despite changes in risk factors and health interventions by eroding access to resources (like money, power, social support, and prestige) that shape one's ability to engage in health-enhancing behaviors, disrupting psychological and behavioral processes that influence health behaviors, and increasing exposure to stress which is associated with numerous health-harming physiological responses (Phelan et al., 2010; Link & Phelan, 1995). In other words, when resources are unevenly distributed, health disparities are more pervasive. When resources are more evenly distributed, disparities in health are reduced.

Scholars propose a number of mechanisms by which social determinants such as working conditions impact the mental health of workers at the lower end of the social gradient. These mechanisms include chronic stress from navigating everyday circumstances, anxiety about insecure and unpredictable living and working conditions, and a perceived lack of control (Fisher & Baum, 2010). Moreover, studies show unemployment, precarious employment, and employment conditions are consistently linked to increased psychological distress which can negatively impact mental health (Han & Lee, 2015; Reibling et al., 2017).

Applying FCT to state labor preemption and mental health suggests that the prevention or suppression of local authorities from universally distributing resources or creating more equitable working conditions may increase risk factors for poor mental health such as financial strain, economic hardship, unpredictable working conditions, and stress. This is particularly relevant in the US where states play an important role in shaping the working conditions that influence mental health (e.g., Grusky et al., 2015; Montez et al., 2017; Montez et al., 2019).

Because states vary markedly in their labor policies, distribution of resources, and opportunity structures, it is critical to assess how state labor policies potentially lead to disparities in mental health. For example, state and local governments that increase minimum wages ensure workers are sufficiently compensated to meet their basic economic needs (Fairris & Reich, 2005). Workers without sufficient compensation may experience economic hardship and financial strain often linked to a number of physical, cognitive, and psychological stressors (Lynch, Kaplan, & Shema, 1997) that are associated with maladaptive health behaviors and physiological responses that can compromise mental health (Burgard & Lin, 2013; Link & Phelan, 1995).

This framework is supported by a robust literature that finds state differences in policies regulating employment and labor conditions have important implications for worker's health and well-being. For instance, increases in state minimum wage rates are associated with improved infant health outcomes including decreases in low birth weight and postneonatal mortality (Komro et al., 2016), reductions in heart disease deaths (Van Dykea et al., 2018), decreases in functional limitations (Andreyeva & Ukert, 2018), improvements in self rated health for non-White groups and women (Andreyeva & Ukert, 2018), and decreases in suicide (Dow et al., 2020). State paid family leave laws are associated with improvements in infant and child health outcomes including decreases in infant and mother rehospitalizations (Jou et al., 2018), longer duration of breastfeeding (Huang & Yang 2015; Appelbaum & Milkman, 2011), as well as reductions in neonatal and child mortality, low birth weight, and premature birth (Stearns, 2015; Rossin, 2011). Paid sick leave mandates are associated with improvements in health, reduced influenza-like illness transmission and mortality rates (Pichler et al., 2021) as well as increases in health care utilization (Peipins et al., 2021; DeRigne et al., 2017). And, fair scheduling laws are associated with improvements in workers' subjective well-being, sleep quality, and economic security (Harknett et al., 2021).

While emerging research has begun to document preemption's health harming concerns (Melton-Fant, 2020; Wolf, Monnat & Montez, 2021), less is known about the effects of state labor preemption laws on mental health. Thus, I examine the association between four state labor preemption laws and mental health outcomes among US workers aged 18-64 and consider how outcomes vary by worker's gender, race and education.

Dimensions of Labor Laws and Worker's Mental Health

Different dimensions of state labor policies may have important heterogeneous effects on worker's health and mental health. Scholars have conceptualized these policy dimensions in terms of economic and temporal terms, arguing that wages *and* work hours matter for health (Schneider & Harknett, 2019; Carre & Tilly, 2018; Kalleberg, 2011). For instance, minimum wage and prevailing wage laws shape wages and affect worker's earning capacity and financial security. Fair scheduling laws, on the other hand, regulate employee's work schedule and protect worker's time while paid leave laws offer both temporal and economic protections.

Despite the overwhelming empirical attention often paid to the health effects of wage-related policies only, research shows temporal aspects of labor laws may be a more important, albeit understudied, determinant of health and well-being that is worthy of more scholarly attention (Schneider & Harknett, 2019). Shaped by labor policy contexts, worker's time (e.g., work time, schedules) is associated with improved quality of life, subjective well-being (for a review see Mogilner, Whillans & Norton, 2018), and a lack of control over work-related time. All of these factors are shown to negatively impact healthy behaviors like diet and exercise (Allen & Armstrong, 2006) and increase stress and depression (Park et al., 2020; Li, 2019). This is supported by research that finds irregular and non-standard work hours are associated with anxiety, depression (Bara & Arber, 2009), poor self-rated health and mental health (Cho, 2017), psychological distress, poor sleep quality, and unhappiness (Schneider & Harknett, 2019) as well as child outcomes including behavioral problems (Pilarz, 2021) and reduced enrollment in early care and education programs (Pilarz et al., 2019).

As such, I also examined the association between economic and temporal dimensions of state preempted labor laws and mental health outcomes to understand how different forms of preemption may be shaping mental health. Results could have important implications for targeted policymaking as well as worker's health and well-being.

Aims

This study examined whether (1) state preemption of four labor laws—minimum wage, prevailing wage, paid leave and fair scheduling—was associated with adverse mental health outcomes for US workers aged 18-64, and (2) whether mental health outcomes differed by economic or temporal dimensions of state labor preemption. I also assessed (3) whether outcomes varied by worker's gender, income, race/ethnicity, and education based on evidence that preemption may disproportionately affect certain subgroups of workers. I hypothesized that increases in the number of state preempted labor laws would be associated with poor mental health outcomes for workers, and workers living in states with preempted temporal-based labor laws would be at increased odds of poor mental health relative to workers living in states that had enacted either no preemption or state preemption of economic-based labor laws only.

Methods

Data

This study merged two datasets on mental health outcomes and state preemption laws. I used 2019 data from the Behavioral Risk Factor Surveillance System (BRFSS) Survey, a nationally representative survey that collects annual state data on the health-related risk behaviors, chronic health conditions, and use of preventive services of US residents aged 18 or older in all 50 states as well as the District of Columbia (Centers for Disease Control and Prevention, 2019). Data from 49 states were included in this study as BRFSS excluded New Jersey in its 2019 data collection. The BRFSS survey is administered by landline telephone or cellular telephone to randomly selected, non-institutionalized adults. In 2019, BRFSS collected data on 418,268 individuals with a median overall response rate of 49.4% (Centers for Disease Control and Prevention, 2020).

Data on state labor preemption laws was aggregated by The Economic Policy Institute (2019), which analyzed state labor preemption laws in all 50 states from 1984 to 2019. The four labor laws used in this study were (1) state minimum wage preemption laws that prohibit cities and counties from establishing minimum wages above the state or federal minimum wage (n=26 states), (2) State paid leave preemption laws which prohibit localities from requiring employers to provide employees paid sick days or paid family leave (n=23 states), (3) State fair scheduling preemption laws which restrict local governments from governing work schedules (n=9 states); and state prevailing wage preemption laws which prohibit localities from requiring municipal contractors to pay workers a prevailing wage of at least the local median wage for a given type of work (n=11 states) (Economic Policy Institute, 2019).

Analytic Sample

The analytic sample was restricted to employed individuals of working age (18-64) (n=146,692). Although prior studies restricted their samples to individuals with a high school education or less in an effort to capture workers most likely impacted by these types of policies (Horn et al., 2017; Leigh et al., 2019; Wehby et al., 2020; Kuroki, 2021) (i.e. low skilled workers), this study assessed for variation in mental health outcomes for workers at all education levels given evidence that declines in health among higher-educated groups and white women in particular have increased in recent decades (Montez et al., 2011; Montez & Zajacova, 2013). As a sensitivity measure, I stratified all models by education categories to assess for potential variation in mental health outcomes for workers with a high school education or less specifically. After excluding individuals with missing information on variables used in the analysis as described below which included income (n=3,092), race/ethnicity (n=18,582), education (n=20,451), and gender (n=20,702), the final analytic sample consisted of 125,990 individuals in all US states except New Jersey. Note, the number of dropped respondents for each of the variables described here are unduplicated. Respondents may be missing on one or more variables.

Measures

Self-Reported Mental Health

The primary outcome variable was self-reported mental health, a valid measure shown to be significantly associated with mental health disorders (Hoff et al., 1997), need for mental health care (Zuvekas & Fleishman, 2008), service utilization (Nabalamba & Millar, 2007), and adherence to treatment plans (Olfson et al., 2006). Self-reported mental health was captured using a dichotomous measure of good or poor mental health based on the number of days respondents reported their mental health as bad in the past 30 days. I used a cut off of 14 days where individuals who reported their mental health as bad for 14 days or more were categorized as having ‘poor mental health’ and individuals who reported their mental health as bad for less than 14 days were considered to be in ‘good mental health’. Studies show a cutoff of 14 or more days is a good indication of clinical depression (Miyakado-Steger & Seidel, 2019; Jiang & Hesser, 2011). Additionally, I used a dichotomous measure of whether or not participants received a doctor's diagnosis of depression in sensitivity analyses (see Appendix, Tables A.1-A.4).

State Preemption of Labor Laws

I used two different state preemption indicators: (1) the number of preempted labor laws for each state, and (2) the type of preemption enacted in each state. First, I measured the number of state enacted labor preemption based on state restriction of any local minimum wage, paid leave, fair scheduling, or prevailing wage laws as of 2019. For each state, I summed the total number of preemptive actions and assigned a score 0, 1, or 2+ laws. Second, to assess whether different dimensions of state labor preemption laws differentially shaped workers’ mental health, I created a categorical preemption dimension variable that categorized states as having no preemption of any labor laws, economic-based preemption only, or economic- *and* temporal-based preemption. No state had enacted temporal-based preemption alone. Temporal-based policies refer to those regulating work schedule predictability and the length and intensity of working hours (Julia et al., 2017). In this study, fair scheduling laws were the only temporal-based preemption law that fit within this domain. Economic-based labor policies encompassed material and wage-related benefits associated with employment (Julia et al., 2017) and included minimum wage, paid leave, and prevailing wage laws. Appendix Table A.13 shows the preemption laws enacted for each state as of 2019.

Covariates

I included a number of basic individual-level characteristics including gender (male or female), age (18-24, 25-34, 35-44, 45-54, 55-64), marital status (married or not), race/ethnicity (White, Black, Hispanic, Other), education (less than high school, high school, some college, college graduate), whether the respondent had children (0 children or 1+ children), and whether the respondent had health care coverage in 2019 (coverage or no coverage) (Kuroki, 2021). I also included a dichotomous measure of household income where the low-income group consisted of single adult households that reported an annual income below $20,000 or households with 2 or more people that reported an annual income below $50,000 in 2019 similar to Kuroki's (2021) study that dealt with the limitations of BRFSS' income categories (<$20,000, <$50,000, <$75,000, $75,000+).

Analytic Strategy

Estimates were weighted according to BRFSS' complex sampling design (Centers for Disease Control and Prevention, 2019) and analyses were conducted using STATA's *svy* suite of commands (StataCorp, 2019). Given evidence that labor policies impact the health of men and women differently (Bullinger, 2019; Horn et al., 2017; Averett et al., 2017), separate analyses were conducted for the sample of male and female workers. First, weighted descriptive statistics were conducted to describe the analytic sample (Table 1.1) and weighted bivariate analyses were conducted to examine associations between each indicator of state labor preemption and mental health for men and women separately (Table 1.2). Next, I employed weighted multivariate logistic regression models while accounting for clustering of standard errors at the state level, consistent with other studies that examined state-level policies on individual-level outcomes (Loll & Hall, 2019; Melton-Fant, 2020) (Table 1.3 and 1.4). Models were adjusted for covariates using AIC, a goodness of fit estimate. To assess for variation in mental health outcomes among subgroups, models were stratified by income, race, and education (i.e., creating an interaction effect) and presented separately for men and women. Predicted probabilities were calculated based on multivariate logistic regression models where associations were statistically significant (Table 1.5). Results from the logistic regression models are presented as odds ratios (OR) with 95% confidence intervals (CI).

Results

Table 1.1 shows the majority of the weighted analytic sample consisted of male workers (53.7%) as compared to female workers (46.3%), and for both sexes the largest percentage of workers fell between 25 and 34 years old (27.1% of the male sample and 25.9% of the female sample, respectively). Female workers with some college education comprised a larger proportion of the sample (32.1%) as compared to male workers (29.6%). More than half of females (69.7%) had incomes of less than $20,000 when in a single adult household and less than $50,000 when in households with 2 or more adults as compared to 25.7% of males. The majority of the sample identified as white (61.9% of men and 61.5% of women) followed by Hispanic (19.4% of men and 16.0% of women), Black (10.2% of men and 14.2% of women), or other race (8.5% of men and 8.4% of women). Females were more likely to have children (49.3%) as compared to their male counterparts (45.2%) and the majority of men and women were married (54.9% and 50.7%, respectively). A large proportion of males (86.4%) and females (89.7%) had health care coverage. Approximately 14.3% of females self-reported their mental health as poor as compared to 9.6% of males, and the largest proportion of male workers lived in states with no preemption (38.9%) as compared to the largest proportion of female workers that lived in states that had preempted two or more labor laws (39.3%). The majority of males and females lived in states that had enacted preemption laws with economic dimensions (43% of male workers and 42.8% of female workers, respectively).

Table 1.2 presents weighted bivariate analyses of the association between each state preemption variable and poor mental health for the samples of men and women, separately. For men and women, the highest percentages of poor mental health occurred in states with 2 or more preempted labor policies (10.3% for men and 15.7% for women, respectively). This association was only statistically significant for female workers. Similarly, both male and female workers that lived in states with economic *and* temporal based preemption reported the highest percentage of poor mental health which was statistically significant for both groups (10.8% for men and 16.1% for women, respectively).

In tables 1.3 and 1.4, I present results from the weighted multivariate logistic regression models for each state preemption variable on poor mental health for men and women separately, after adjusting for gender, age, education, income, race, marital status, children, and health coverage (see tables with full controls in Appendix, Tables A.9-A.12). Table 1.5 provides predicted probabilities for outcomes that were statistically significant in the multivariate logistic regression models.

State Preemption and the Mental Health of Female Workers

Results from the weighted logistic regressions indicate female workers that lived in states with 2 or more preempted labor laws were at increased odds of reporting poor mental health as compared with women that lived in states with no preemption or only 1 preemption law (Table 1.3). Although the likelihood of poor mental health increased for all subgroups of female workers that lived in states with 2 or more preemption laws, the association was statistically significant for the full sample of female workers and for Hispanic female workers only (Table

1.3). As shown in Table 1.5, the full sample of female workers that lived in states with 2 or more preempted labor laws had a 15.4% probability of reporting poor mental health as compared to a predicted probability of 14.4% for female workers that lived in states with no preemption (Table 1.5).

When considering the effects of state preemption on poor mental health across racial groups, I found that the mental health of Hispanic female workers was significantly more likely to be rated poor as the number of enacted state preemption laws increased (Table 1.3). Put another way, Hispanic female workers who lived in states that enacted 2 or more preemption laws had a 18.7% probability of reporting poor mental health as compared to female workers in states with 0 preemption laws who had a 16.6% probability of reporting poor mental health (Table 1.5). Although the odds of reporting poor mental health increased for both white female workers and female workers who identified as other race that lived in states with 2 or more preemption laws, the associations were not statistically significant (Table 1.3).

Additionally, results suggest that education may play an important role in shaping the mental health of female workers that lived in states with more labor preemption laws (Table 1.3). Although the associations were not statistically significant, the odds of reporting poor mental health increased as the level of education attained decreased. For instance, female workers with less than a high school education had the highest odds of poor mental health, followed by workers with a high school education, and then female workers with some college education (Table 1.3).

I also considered whether mental health outcomes varied for female workers living in states that had enacted different types of preempted labor laws (i.e. laws with economic or temporal dimensions). For the full sample of women, results show that preemption of both economic and temporal-based labor laws significantly increased the likelihood of poor mental health, whereas a state that solely enacted economic-based preemption did not appear to have a statistically significant effect on mental health (Table 1.3). In other words, female workers in states with economic *and* temporal based preemption laws had a 16.8% probability of reporting poor mental health as compared to 14.9% of female workers that lived in states with economic based preemption only (Table 1.5).

In subgroup analyses, economic and temporal dimensions of state preemption significantly increased the odds of poor mental health for low income and Hispanic female workers, and the likelihood of poor mental health significantly increased for low income and Hispanic female workers that lived in states that had enacted economic as well as temporal-based labor preemption (Table 1.3). Put another way, the probability of reporting poor mental health was 3 and 2.8 percentage points higher for low income and Hispanic female workers that lived in states that enacted temporal-based preempted labor laws, in addition to economic-based preemption, than those who lived in states with economic-based labor preemption only (Table 1.5).

Finally, when stratified by education, a similar pattern emerged as described above for female workers living in states with economic and temporal dimensions of preemption such that the odds of reporting poor mental health increased as the level of education attained decreased for women that lived in states with both types of preemption laws (Table 1.3).

State Preemption and the Mental Health of Male Workers

When considering the association between state labor preemption and poor mental health for male workers, I found no statistically significant associations between any amount or type of state preemption and poor mental health when covariates were introduced in the multivariate logistic regression models (Table 1.4) despite evidence of a statistically significant relationship between dimensions of state preemption and poor mental health in the bivariate analyses (Table 1.2). Thus, findings suggest the mental health consequences of state preemption disproportionately impact female workers.

Sensitivity Analyses

In sensitivity analyses, I considered an alternative indicator of poor mental health using a measure of a doctor's diagnosis of depression (see Appendix, Tables A.1-A.4). Similar to findings in the main analysis, the odds of a reported doctor's diagnosis of depression significantly increased for the full sample of female workers who lived in states with 2 or more preemption laws (Appendix, Table A.1) as well as for those who lived in states with economic and temporal dimensions of preemption (Appendix, Table A.2). When stratified by income, the association between 2 or more preemption laws and poor mental health was significant for the sample of high-income women, however the odds were greater among those considered low income despite a lack of statistical significance (Appendix, Table A.1). When stratified by race, results show female workers who identified as other race that lived in states with 2 or more preempted labor laws as well as females of other race who lived in states with temporal based preemption laws were at significantly increased odds of a depression diagnosis as compared to females of other race that lived in states with no preemption (Appendix, Table A.1 and Table A.2). Interestingly, when stratified by education the odds of reporting poor mental health were highest among the sample of female workers with less than a high school education who lived in states with multiple numbers and types of preemption laws, although the association was only statistically significant for the sample of college educated women (Appendix, Tables A.1 and A.2).

In assessing the relationship between state preemption and a doctor's diagnosis of depression for male workers, I found that the full sample of male workers that lived in states with 2 or more preemption laws as well as the samples of low income, other race, and high school educated male workers that lived in states with multiple preemption laws were at significant odds of reporting their mental health as poor (Appendix, Table A.3). Additionally, the full sample of male workers as well as male workers of low income and Hispanic or other race that lived in states with both economic and temporal dimensions of preemption were at significantly increased odds of reporting their mental health as poor (Appendix, Table A.4). Results were somewhat unsurprising given evidence that women are more likely to self-report poor mental health than their male counterparts (Doherty & Kartalova-O'Doherty, 2009) indicating that males may only be identified with mental health problems such as depression when undergoing depression screenings as part of routine health care. Moreover, racial and socioeconomic disparities in access to healthcare and service utilization may impact a mental health diagnosis (Institute of Medicine, 2002; Chen et al., 2016) likely resulting in potential underreports of poor mental health in surveys such as BRFSS.

Finally, I conducted analyses using a continuous measure of the primary outcome variable for self-reported health based on the number of days respondents reported their mental health as bad in the past 30 days. Similar to results from the models using the dichotomous measure of self-reported mental health, analyses indicated that the full sample of female workers living in either states with 2 or more preemption laws or temporal *and* economic dimensions of preemption reported a statistically significant increase in the number of days they experienced poor mental health, and this significant pattern appeared across subgroups of high income and Hispanic female workers as well (Appendix, Tables A.5 and A.6). Of note, a similar pattern appeared for the sample of male workers such that the full sample of male workers as well as high income and college educated samples of male workers that lived in states with 2 or more preemption laws showed a slight, statistically significant increase in the number of days mental health was reported poor over a 30 day period (Appendix, Table A.7). The full sample of male workers that lived in states with economic and temporal dimensions of preemption as well as the sample of Hispanic male workers and those with less than a high school education experienced significant increases in the number of days they reported their mental health as poor as compared to their male counterparts (Appendix, Table A.8). Findings were somewhat consistent with outcomes from models using a dichotomous measure of self-reported mental health, however utilizing the dichotomous measure of self-reported mental health that is often used in studies assessing BRFSS data (Miyakado-Steger & Seidel, 2019; Jiang & Hesser, 2011) may underestimate the mental health of some male workers, particularly those living in states that have enacted various labor preemption laws, and in fact these groups may experience similar mental health outcomes to their female counterparts although at a much slighter likelihood in the number of reported days of poor mental health.

Discussion

This study examined whether state preemption of four labor laws including minimum wage, prevailing wage, paid leave, and fair scheduling were associated with poor mental health for male and female workers, and whether these outcomes differed for workers living in states that preempted economic- versus temporal-based labor laws. To the best of my knowledge, this is the first study to consider gender-, race- and SES- effects of state labor preemption on worker's mental health. This study offers a number of new insights about the relationship between state preemption and mental health, particularly for female workers of all education levels despite a history of scholarly focus on the health effects of similar labor policies on low skilled workers only, or those with a high school education or less.

First, this study found that increases in and different forms of state preempted labor laws was associated with poor mental health for female workers, and particularly those with very low incomes as well as Hispanic women. I found no evidence that state preemption of any of the four labor laws included in this study were associated with adverse mental health outcomes for men, consistent with previous literature showing some labor laws like minimum wage appear to have a greater effect on the mental health of low skilled female workers but may have little to no effect on the mental health of male workers (Horn et al., 2017). Importantly, findings contribute to emerging evidence that hyper preemption is associated with health harming consequences (Carr et al., 2020; Montez, 2020; Wolf et al., 2021; Melton-Fant, 2020) and contribute new information about the association between preemption and mental health.

The disproportionate negative mental health effects of state preemption for low-income female workers is both notable and unsurprising given women's position in the workforce. Evidence shows women are more likely to be employed in low-wage sectors (BLS, 2017) and account for a larger proportion of the workforce paid below the minimum wage (BLS, 2017; Narian & Zimmerman, 2019). Additionally, low wage workers are the least likely subgroup to receive essential benefits such as paid leave from their employers (Ponce et al., 2008). As a result, states that restrict opportunities for local minimum wage increases or paid leave benefits, for instance, are shown to impose financial strain and stress (Reeves et al., 2017) that can manifest in mental health consequences for female workers most impacted by these policy outcomes.

Results also suggest Hispanic female workers are disproportionately affected by state labor preemption laws and are more likely to report poor mental health when living in states that have preempted two or more labor laws relative to Hispanic female workers that lived in states with no preemption. This finding aligns with research that shows Hispanic groups make up a larger and growing proportion of the low-skilled workforce in the US. In particular, Hispanic women are more concentrated in low-paid jobs (Orrenius & Zavodny, 2010; Alonso-Villar, Rio, & Gradin, 2012) and as a result may be disproportionately affected by labor laws related to minimum wages and unpredictable work schedules.

This study also found that state preemption of temporal-based labor laws, in other words laws that shape work schedule predictability and the length and intensity of working hours, increased the likelihood of poor mental health for all female workers as well as low income and Hispanic women specifically. This finding supports growing concerns that economic aspects of labor laws may be less potent in shaping health than often proposed and supports empirical and theoretical evidence that temporal aspects of labor laws may actually be a stronger predictor of worker's health and well-being (Schneider & Harknett, 2019) due to work-life conflict (Golden, 2015) and income volatility (Leete & Bania, 2010; Wight et al., 2008) often faced by female workers faced with unpredictable and unstable work schedules (Ben-Ishai, 2015; Golden, 2015). Considering different dimensions of preemption as well as the pathways linking different aspects of these laws to health inequities should be a larger focus in future research efforts.

This study has important implications for state governments and policymakers that aim to protect the health and well-being of their workforce. First, the study supports growing concerns that increases in state preemption may have significant consequences for population health (Carr et al., 2020; Crosbie & Schmidt, 2020; Montez, 2020; Pomeranz & Pertschuk, 2017; Wolf et al., 2021). Additionally, this study highlights the importance of considering upstream factors such as state policy contexts for addressing the conditions that affect population health (e.g., Grusky et al., 2015; Montez et al., 2017; Montez et al., 2019). Furthermore, this study advances a health in all policies agenda for promoting equity.

While this study is an important first step in exploring the relationship between state preempted labor laws and mental health, limitations exist. First, this study is cross-sectional and only considers mental health outcomes at one time point. Future research should consider how state preemption laws shape mental health and well-being over time. Second, while this study provides insight about associations between state preemption and health, it is unable to make causal claims. Innovative and robust methods should be considered in future studies to move beyond descriptive analyses to examine causal relationships and interrogate underlying mechanisms that link state preemption and health. Third, this study examined self-reports of mental health which may be subject to selection and desirability biases. Finally, mental health data used in this study was captured in 2019 before the onset of the global COVID-19 pandemic. In response to the pandemic, targeted state preemption enabled some local efforts to pass public health protections yet blocked the efforts of others. Ongoing research is needed to evaluate how state and federal preemption has shaped population health in light of this context, especially among underserved communities. Additionally, this study does not account for other state-level policies that may be confounding the associations found here. For instance, state Temporary Assistance for Needy Families (TANF) and Medicaid expansion programs may be important state-level controls to consider in future analyses given state discretion in program generosity and the implications this can have for worker’s mental health and well-being, particularly those likely impacted by labor preemption policies as identified here. Finally, it’s worth noting the significant drop in respondents used in this study due to missingness, particularly for gender. It has been estimated that approximately 55% of gender identity data is missing from 2014-2019 BRFSS data due in part to the optional nature of the sexual orientation and gender identity (SOGI) module as well as early interview termination (Jesdale, 2021).

Conclusion

This study examined the relationship between state preemption of four labor laws and mental health outcomes among US workers aged 18-64. Findings show female workers that lived in states with multiple preempted labor laws were at significantly higher odds of reporting poor mental health, with pronounced mental health consequences for Hispanic females. State preemption of temporal-based labor laws significantly increased the likelihood of poor mental health for female workers as compared with states that enacted economic-based preemption only, and this association was pronounced for low-income female workers and Hispanic female workers. Notably, state preemption had no impact on poor mental health outcomes for male workers, suggesting that the mental health consequences of state preemption disproportionately impacts females.

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Tables

Table 1.1. Weighted descriptive statistics for male and female workers separately, presented as weighted percentages.

	Males (%)	**Females (%)**
	Unweighted N= 63,355 (53.7)	Unweighted N= 62,635 (46.3)
Age		
18-24	11.9	10.5
25-34	27.1	25.9
35-44	24.3	24.0
45-54	20.6	21.8
55-64	15.9	17.7
Education		
< High School	10.6	6.2
High School	27.7	20.9
Some College	29.6	32.1
College Graduate	32.2	40.8
Household Income		
Low	25.7	69.7
High	74.3	30.3
Race		
White	61.9	61.5
Black	10.2	14.2
Hispanic	19.4	16.0
Other	8.5	8.4
Children		
No Children	54.9	50.7
1+ Children	45.2	49.3
Relationship Status		
Married	54.9	52.2
Not married	45.1	47.8
Health Care		
Coverage	86.4	89.7
No Coverage	13.6	10.3
Self-Rated Mental Health		
Poor	9.6	14.3
Good	90.5	85.8
Number of State Preemption Laws Enacted		
0	38.9	38.6
1	22.9	22.1
2+	38.2	39.3

Dimensions of Preemption Enacted		
No Preemption	38.9	38.6
Economic Only	43.0	42.8
Economic & Temporal	18.1	18.6

Table 1.2. Weighted bivariate analyses of the association between each state preemption exposure and poor mental health for male and female workers.

	0 Preemption	**1 Preemption Law**	**2+ Preemption Laws**	*p-value*	**0 Preemption**	**Economic Preemption**	**Economic & Temporal Preemption**	*p-value*
	%	%	%		%	%	%	
Women	13.3	13.4	15.7	0.000	13.3	14.1	16.1	0.000
Men	9.0	9.3	10.3	0.052	9.0	9.5	10.8	0.008

Note: Chi-square tests are used to assess associations between each variable.

Table 1.3. Weighted multivariate logistic regression models of state preemption indicators on poor mental health for female workers and by subgroups; Presented as odds ratios.

	Full Sample	Low Income	High Income	White	Black	Hispanic	Other	<High School	High School	Some College	College
	OR (CI)	***OR (CI)***	***OR (CI)***	***OR (CI)***	***OR (CI)***	***OR (CI)***	***OR (CI)***	***OR (CI)***	***OR (CI)***	***OR (CI)***	***OR (CI)***
1 Preemption Law	0.992 (0.868 - 1.133)	1.042 (0.834 - 1.302)	0.953 (0.810 - 1.121)	0.895 (0.771 - 1.039)	0.86 (0.594 - 1.245)	1.444** (1.014 - 2.055)	0.961 (0.604 - 1.527)	0.966 (0.551 - 1.691)	1.058 (0.807 - 1.386)	0.911 (0.715 - 1.161)	0.988 (0.816 - 1.197)
2+ Preemption Laws	1.120** (1.014 - 1.238)	1.137 (0.971 - 1.331)	1.08 (0.953 - 1.224)	1.039 (0.930 - 1.160)	0.941 (0.718 - 1.233)	1.496** (1.067 - 2.099)	1.023 (0.716 - 1.462)	1.647 (0.986 - 2.752)	1.14 (0.928 - 1.400)	1.002 (0.849 - 1.184)	1.098 (0.945 - 1.275)
Economic Preemption	1.024 (0.922 - 1.137)	1.057 (0.893 - 1.251)	0.986 (0.866 - 1.122)	0.94 (0.836 - 1.056)	0.865 (0.649 - 1.152)	1.396** (1.040 - 1.874)	1.014 (0.706 - 1.457)	1.179 (0.752 - 1.849)	1.081 (0.870 - 1.342)	0.897 (0.746 - 1.078)	1.045 (0.897 - 1.217)
Temporal Dimension	1.190*** (1.063 - 1.332)	1.213** (1.010 - 1.456)	1.144 (0.995 - 1.315)	1.096 (0.968 - 1.242)	1.023 (0.753 - 1.391)	1.941*** (1.202 - 3.134)	0.95 (0.601 - 1.501)	1.861 (0.984 - 3.520)	1.176 (0.932 - 1.485)	1.147 (0.954 - 1.379)	1.078 (0.916 - 1.268)

Note: Referent group = No State Preemption of Labor Laws; Control variables include age, education, income, race, relationship status, children, health insurance coverage.
*** p<0.01, ** p<0.05

Table 1.4. Weighted multivariate logistic regression models of state preemption indicators on poor mental health for male workers and by subgroups; Presented as odds ratios.

	Full Sample	Low Income	High Income	White	Black	Hispanic	Other	<High School	High School	Some College	College
	OR (CI)	***OR (CI)***	***OR (CI)***	***OR (CI)***	***OR (CI)***	***OR (CI)***	***OR (CI)***	***OR (CI)***	***OR (CI)***	***OR (CI)***	***OR (CI)***
1 Preemption Law	1.012 (0.867 - 1.181)	1.086 (0.831 - 1.419)	0.955 (0.791 - 1.154)	0.929 (0.791 - 1.091)	0.862 (0.493 - 1.507)	1.256 (0.849 - 1.857)	0.679 (0.423 - 1.089)	0.817 (0.482 - 1.385)	1.07 (0.812 - 1.411)	1.032 (0.785 - 1.356)	0.867 (0.675 - 1.114)
2+ Preemption Laws	1.053 (0.944 - 1.174)	0.934 (0.774 - 1.127)	1.086 (0.949 - 1.242)	1.024 (0.905 - 1.158)	1.108 (0.758 - 1.620)	0.759 (0.532 - 1.082)	1.061 (0.703 - 1.602)	1.024 (0.690 - 1.521)	1.023 (0.848 - 1.234)	1.011 (0.835 - 1.226)	1.056 (0.866 - 1.288)
Economic Preemption	1.005 (0.891 - 1.133)	0.967 (0.785 - 1.192)	1.0 (0.864 - 1.158)	0.957 (0.842 - 1.087)	0.882 (0.585 - 1.328)	1.075 (0.768 - 1.505)	0.915 (0.607 - 1.379)	0.917 (0.618 - 1.363)	1.001 (0.807 - 1.240)	0.987 (0.798 - 1.221)	0.953 (0.776 - 1.170)
Temporal Dimension	1.118 (0.984 - 1.269)	1.045 (0.847 - 1.290)	1.118 (0.955 - 1.309)	1.063 (0.923 - 1.224)	1.336 (0.856 - 2.084)	0.846 (0.544 - 1.316)	0.909 (0.590 - 1.400)	1.002 (0.610 - 1.643)	1.128 (0.910 - 1.399)	1.105 (0.880 - 1.387)	1.054 (0.853 - 1.303)

Note: Referent group = No State Preemption of Labor Laws; Control variables include age, education, income, race, relationship status, children, health insurance coverage.
*** p<0.01, ** p<0.05

Table 1.5. Predicted probabilities of outcomes based on multivariate logistic regression models where associations were statistically significant.

	Women		**Low Income Women**		**Hispanic Women**	
	Predicted Probabilities	***CI***	***Predicted Probabilities***	***CI***	***Predicted Probabilities***	***CI***
0 Preemption Laws	14.4	13.6-15.2	-	-	16.6	15.3-17.8
1 Preemption Law	14.4	13.4-15.5	-	-	16.4	14.7-18.0
2+ Preemption Laws	15.4	14.7-16.1	-	-	18.7	17.4-19.9
0 Preemption Laws	14.6	13.7-15.6	18.0	16.7-19.4	16.6	15.3-17.8
Economic Preemption Laws	14.9	14.0-15.8	18.5	17.2-19.8	17.0	15.8-18.2
Economic & Temporal Preemption Laws	16.8	15.7-18.0	21.5	19.8-23.1	19.8	18.2-21.4

Note: CI = Confidence Interval.

Appendix A

Table A.1. Weighted Multivariate Logistic Regression Models for Number of State Preemption Laws on Doctor Diagnosis of Depression for Women, and by subgroups; Presented as Odds Ratios.

	Full Sample	Low Income	High Income	White	Black	Hispanic	Other	<High School	High School	Some College	College
1 Preemption	1.066 (0.960 - 1.183)	1.095 (0.887 - 1.352)	1.049 (0.930 - 1.183)	1.056 (0.940 - 1.187)	0.76 (0.534 - 1.082)	1.082 (0.792 - 1.477)	1.408 (0.897 - 2.211)	1.033 (0.542 - 1.968)	1.004 (0.783 - 1.287)	1.045 (0.867 - 1.259)	1.107 (0.960 - 1.275)
2+ Preemption	1.137*** (1.052 - 1.228)	1.136 (0.987 - 1.307)	1.116** (1.018 - 1.223)	1.074 (0.988 - 1.167)	0.928 (0.714 - 1.205)	1.155 (0.865 - 1.541)	1.928*** (1.410 - 2.636)	1.23 (0.767 - 1.972)	1.098 (0.922 - 1.309)	1.127 (0.983 - 1.291)	1.114** (1.002 - 1.239)
25-34	0.936 (0.813 - 1.077)	0.985 (0.795 - 1.220)	0.903 (0.744 - 1.096)	0.894 (0.755 - 1.058)	1.415 (0.910 - 2.202)	0.962 (0.652 - 1.418)	0.764 (0.465 - 1.255)	0.604 (0.307 - 1.188)	0.907 (0.673 - 1.220)	1.174 (0.935 - 1.473)	0.95 (0.758 - 1.190)
35-44	0.832** (0.716 - 0.967)	0.876 (0.692 - 1.109)	0.804** (0.657 - 0.983)	0.774*** (0.649 - 0.923)	1.131 (0.718 - 1.782)	0.966 (0.630 - 1.479)	0.974 (0.563 - 1.686)	0.483** (0.250 - 0.935)	0.727** (0.532 - 0.994)	0.906 (0.713 - 1.152)	1.048 (0.827 - 1.327)
45-54	0.681*** (0.590 - 0.785)	0.790** (0.635 - 0.983)	0.640*** (0.527 - 0.777)	0.665*** (0.562 - 0.787)	0.923 (0.573 - 1.488)	0.668* (0.443 - 1.006)	0.705 (0.409 - 1.215)	0.362*** (0.196 - 0.669)	0.692** (0.515 - 0.929)	0.696*** (0.555 - 0.873)	0.848 (0.672 - 1.070)
55-64	0.564*** (0.487 - 0.654)	0.520*** (0.416 - 0.649)	0.577*** (0.472 - 0.704)	0.559*** (0.473 - 0.660)	0.716 (0.442 - 1.159)	0.566* (0.320 - 1.003)	0.442** (0.205 - 0.952)	0.173*** (0.089 - 0.336)	0.451*** (0.337 - 0.603)	0.612*** (0.485 - 0.773)	0.792* (0.618 - 1.015)
High School	0.874 (0.712 - 1.072)	0.799* (0.627 - 1.017)	0.708 (0.463 - 1.083)	0.644*** (0.486 - 0.853)	0.724 (0.414 - 1.265)	0.856 (0.554 - 1.322)	1.596 (0.767 - 3.322)				
Some College	1.019 (0.834 - 1.244)	1.049 (0.833 - 1.321)	0.76 (0.500 - 1.155)	0.722** (0.547 - 0.953)	1.078 (0.633 - 1.834)	1.088 (0.722 - 1.641)	1.309 (0.663 - 2.583)				
College Grad	0.809** (0.659 - 0.994)	0.788* (0.614 - 1.012)	0.629** (0.415 - 0.954)	0.573*** (0.433 - 0.757)	0.828 (0.481 - 1.426)	1.14 (0.727 - 1.788)	1.027 (0.506 - 2.084)				
Low Income	1.110** (1.016 - 1.213)			1.217*** (1.102 - 1.343)	1.371** (1.062 - 1.769)	0.761** (0.580 - 0.999)	0.819 (0.590 - 1.137)	0.863 (0.514 - 1.451)	0.994 (0.843 - 1.173)	1.245*** (1.087 - 1.426)	1.144* (0.989 - 1.323)
Black	0.371*** (0.328 - 0.420)	0.350*** (0.286 - 0.429)	0.370*** (0.316 - 0.432)					0.279*** (0.155 - 0.504)	0.305*** (0.233 - 0.400)	0.392*** (0.319 - 0.482)	0.384*** (0.317 - 0.466)
Hispanic	0.482*** (0.419 - 0.554)	0.339*** (0.279 - 0.412)	0.655*** (0.544 - 0.787)					0.316*** (0.191 - 0.522)	0.379*** (0.285 - 0.502)	0.464*** (0.370 - 0.582)	0.763** (0.606 - 0.960)

Other	0.487***	0.373***	0.543***					0.229***	0.578***	0.471***	0.499***
	(0.414 - 0.572)	(0.292 - 0.477)	(0.443 - 0.667)					(0.109 - 0.478)	(0.383 - 0.873)	(0.369 - 0.601)	(0.389 - 0.639)
Married	0.612***	0.590***	0.631***	0.614***	0.726**	0.639***	0.540***	0.688*	0.628***	0.632***	0.582***
	(0.567 - 0.661)	(0.509 - 0.684)	(0.576 - 0.691)	(0.565 - 0.667)	(0.543 - 0.973)	(0.495 - 0.825)	(0.386 - 0.753)	(0.456 - 1.039)	(0.525 - 0.751)	(0.552 - 0.723)	(0.522 - 0.648)
Children	0.98	0.915	1.022	0.991	1.228	0.943	0.776	0.738	0.995	1.023	0.923
	(0.905 - 1.062)	(0.785 - 1.067)	(0.929 - 1.123)	(0.906 - 1.083)	(0.954 - 1.582)	(0.715 - 1.244)	(0.559 - 1.077)	(0.456 - 1.196)	(0.818 - 1.210)	(0.886 - 1.181)	(0.827 - 1.030)
Health Coverage	0.98	0.995	0.908	0.854**	1.096	1.061	1.002	1.203	0.894	0.923	1.077
	(0.859 - 1.118)	(0.838 - 1.182)	(0.741 - 1.113)	(0.734 - 0.993)	(0.736 - 1.632)	(0.764 - 1.474)	(0.623 - 1.613)	(0.802 - 1.805)	(0.704 - 1.137)	(0.750 - 1.136)	(0.829 - 1.399)
Constant	0.638***	0.797	0.856	1.036	0.146***	0.308***	0.252***	1.731	0.727*	0.579***	0.402***
	(0.485 - 0.837)	(0.584 - 1.088)	(0.521 - 1.406)	(0.733 - 1.466)	(0.065 - 0.327)	(0.167 - 0.570)	(0.101 - 0.629)	(0.780 - 3.842)	(0.518 - 1.019)	(0.426 - 0.789)	(0.287 - 0.565)
Observations	407,819	397,916	407,201	406,521	290,552	320,714	328,333	289,473	395,118	400,529	404,688

Note: Referent group = No State Preemption of Labor Laws; Control variables include age, education, income, race, relationship status, children, health insurance coverage.
*** $p<0.01$, ** $p<0.05$

Table A.2. Weighted multivariate logistic regression models of state preemption dimensions on doctor diagnosis of depression for females, and by subgroups; Presented as odds ratios.

	Full Sample	Low Income	High Income	White	Black	Hispanic	Other	<High School	High School	Some College	College
Economic Preemption	1.113*** (1.026 - 1.206)	1.109 (0.951 - 1.294)	1.102** (1.002 - 1.212)	1.076 (0.984 - 1.175)	0.874 (0.667 - 1.146)	1.082 (0.838 - 1.398)	1.728*** (1.242 - 2.405)	1.077 (0.676 - 1.717)	1.043 (0.862 - 1.261)	1.109 (0.961 - 1.281)	1.130** (1.011 - 1.264)
Economic + Temporal	1.105** (1.011 - 1.208)	1.149 (0.973 - 1.357)	1.064 (0.958 - 1.181)	1.053 (0.958 - 1.157)	0.884 (0.650 - 1.200)	1.321 (0.850 - 2.053)	1.614** (1.088 - 2.394)	1.330 (0.731 - 2.420)	1.109 (0.905 - 1.358)	1.076 (0.922 - 1.255)	1.065 (0.945 - 1.199)
25-34	0.934 (0.812 - 1.075)	0.985 (0.795 - 1.220)	0.898 (0.741 - 1.090)	0.893 (0.754 - 1.056)	1.424 (0.912 - 2.224)	0.959 (0.651 - 1.413)	0.762 (0.464 - 1.251)	0.598 (0.306 - 1.169)	0.908 (0.674 - 1.223)	1.168 (0.931 - 1.467)	0.947 (0.756 - 1.187)
35-44	0.832** (0.716 - 0.966)	0.877 (0.693 - 1.110)	0.801** (0.656 - 0.980)	0.773*** (0.649 - 0.922)	1.144 (0.725 - 1.806)	0.969 (0.633 - 1.482)	0.967 (0.558 - 1.675)	0.484** (0.251 - 0.931)	0.730** (0.533 - 0.999)	0.905 (0.712 - 1.151)	1.045 (0.826 - 1.323)
45-54	0.679*** (0.589 - 0.783)	0.790** (0.635 - 0.983)	0.637*** (0.525 - 0.773)	0.664*** (0.561 - 0.786)	0.928 (0.574 - 1.501)	0.670* (0.446 - 1.007)	0.685 (0.396 - 1.184)	0.358*** (0.194 - 0.661)	0.692** (0.515 - 0.930)	0.693*** (0.553 - 0.869)	0.846 (0.671 - 1.067)
55-64	0.563*** (0.486 - 0.652)	0.519*** (0.416 - 0.648)	0.574*** (0.470 - 0.700)	0.558*** (0.472 - 0.659)	0.717 (0.442 - 1.165)	0.569* (0.323 - 1.005)	0.436** (0.202 - 0.939)	0.172*** (0.089 - 0.333)	0.451*** (0.337 - 0.603)	0.609*** (0.483 - 0.769)	0.791* (0.617 - 1.013)
High School	0.870 (0.709 - 1.067)	0.798* (0.627 - 1.016)	0.705 (0.460 - 1.080)	0.642*** (0.485 - 0.851)	0.719 (0.409 - 1.262)	0.859 (0.558 - 1.323)	1.576 (0.753 - 3.299)				
Some College	1.016 (0.832 - 1.241)	1.049 (0.834 - 1.321)	0.758 (0.498 - 1.153)	0.720** (0.546 - 0.951)	1.081 (0.633 - 1.847)	1.097 (0.731 - 1.647)	1.312 (0.662 - 2.601)				
College Grad	0.806** (0.656 - 0.989)	0.788* (0.614 - 1.012)	0.626** (0.412 - 0.950)	0.571*** (0.432 - 0.755)	0.825 (0.476 - 1.427)	1.152 (0.740 - 1.794)	0.998 (0.489 - 2.036)				
Low Income	1.113** (1.019 - 1.216)			1.218*** (1.104 - 1.345)	1.384** (1.074 - 1.785)	0.762** (0.582 - 0.999)	0.817 (0.588 - 1.135)	0.869 (0.523 - 1.445)	0.996 (0.844 - 1.174)	1.249*** (1.090 - 1.430)	1.145* (0.990 - 1.325)
Black	0.371*** (0.328 - 0.420)	0.350*** (0.286 - 0.430)	0.370*** (0.317 - 0.432)					0.277*** (0.154 - 0.499)	0.306*** (0.233 - 0.401)	0.393*** (0.319 - 0.484)	0.385*** (0.317 - 0.467)
Hispanic	0.477*** (0.415 - 0.548)	0.339*** (0.278 - 0.413)	0.647*** (0.538 - 0.778)					0.314*** (0.187 - 0.527)	0.376*** (0.283 - 0.498)	0.458*** (0.365 - 0.575)	0.756** (0.602 - 0.950)
Other	0.485*** (0.412 - 0.571)	0.373*** (0.292 - 0.477)	0.541*** (0.441 - 0.665)					0.230*** (0.110 - 0.482)	0.579*** (0.383 - 0.875)	0.470*** (0.369 - 0.600)	0.497*** (0.388 - 0.637)
Married	0.612***	0.590***	0.631***	0.614***	0.725**	0.638***	0.542***	0.689*	0.629***	0.632***	0.582***

	(0.567 - 0.662)	(0.509 - 0.684)	(0.576 - 0.691)	(0.565 - 0.667)	(0.540 - 0.974)	(0.495 - 0.822)	(0.388 - 0.757)	(0.457 - 1.040)	(0.527 - 0.752)	(0.552 - 0.723)	(0.523 - 0.649)
Children	0.980	0.914	1.023	0.992	1.225	0.942	0.788	0.732	0.994	1.022	0.924
	(0.905 - 1.062)	(0.784 - 1.066)	(0.930 - 1.124)	(0.907 - 1.084)	(0.951 - 1.578)	(0.715 - 1.242)	(0.568 - 1.095)	(0.453 - 1.181)	(0.817 - 1.209)	(0.885 - 1.181)	(0.828 - 1.030)
Health Coverage	0.981	0.995	0.909	0.854**	1.098	1.059	1.001	1.198	0.894	0.926	1.078
	(0.860 - 1.120)	(0.837 - 1.182)	(0.741 - 1.115)	(0.734 - 0.993)	(0.736 - 1.638)	(0.762 - 1.472)	(0.616 - 1.627)	(0.797 - 1.801)	(0.703 - 1.136)	(0.752 - 1.140)	(0.830 - 1.401)
Constant	0.640***	0.798	0.863	1.039	0.145***	0.307***	0.257***	1.750	0.727*	0.580***	0.403***
	(0.488 - 0.841)	(0.586 - 1.088)	(0.525 - 1.419)	(0.735 - 1.471)	(0.064 - 0.326)	(0.167 - 0.565)	(0.102 - 0.647)	(0.788 - 3.885)	(0.518 - 1.020)	(0.426 - 0.790)	(0.287 - 0.566)
Observations	407,819	397,916	407,201	406,521	290,552	320,714	328,333	289,473	395,118	400,529	404,688

Note: Referent group = No State Preemption of Labor Laws; Control variables include age, income, education, race, relationship status, children, health insurance coverage.
*** p<0.01, ** p<0.05.

Table A.3. Weighted Multivariate Logistic Regression Models for Number of State Preemption Laws on Doctor Diagnosis of Depression for Males, by subgroups; Presented as Odds Ratios.

	Full Sample	Low Income	High Income	White	Black	Hispanic	Other	<High School	High School	Some College	College
1 Preemption	1.046 (0.921 - 1.188)	1.075 (0.829 - 1.395)	1.026 (0.887 - 1.186)	1.038 (0.906 - 1.191)	0.849 (0.456 - 1.581)	1.062 (0.723 - 1.561)	0.757 (0.481 - 1.192)	0.700 (0.423 - 1.158)	1.131 (0.873 - 1.466)	1.062 (0.839 - 1.346)	1.031 (0.863 - 1.232)
2+ Preemption	1.112** (1.013 - 1.220)	1.258** (1.054 - 1.502)	1.046 (0.937 - 1.167)	1.053 (0.952 - 1.164)	0.983 (0.648 - 1.492)	1.199 (0.847 - 1.696)	1.455** (1.028 - 2.061)	0.948 (0.617 - 1.459)	1.213** (1.019 - 1.443)	1.108 (0.930 - 1.319)	1.026 (0.898 - 1.173)
25-34	1.116 (0.963 - 1.293)	1.056 (0.847 - 1.317)	1.191* (0.974 - 1.457)	1.283*** (1.091 - 1.510)	1.451 (0.810 - 2.597)	0.648* (0.416 - 1.009)	0.876 (0.527 - 1.456)	0.749 (0.418 - 1.343)	1.058 (0.843 - 1.329)	1.286* (0.987 - 1.675)	1.643*** (1.239 - 2.179)
35-44	1.110 (0.940 - 1.310)	1.001 (0.751 - 1.334)	1.218* (0.981 - 1.511)	1.203** (1.005 - 1.439)	1.341 (0.687 - 2.615)	0.933 (0.549 - 1.586)	0.967 (0.523 - 1.785)	0.587* (0.320 - 1.074)	1.016 (0.769 - 1.342)	1.409** (1.045 - 1.901)	1.723*** (1.263 - 2.351)
45-54	0.885 (0.748 - 1.049)	0.786* (0.595 - 1.040)	0.985 (0.790 - 1.228)	0.992 (0.826 - 1.192)	1.081 (0.545 - 2.145)	0.617 (0.340 - 1.118)	0.869 (0.473 - 1.596)	0.502** (0.274 - 0.920)	0.763* (0.562 - 1.035)	1.024 (0.749 - 1.398)	1.542*** (1.139 - 2.088)
55-64	0.803** (0.676 - 0.955)	0.727** (0.532 - 0.994)	0.896 (0.719 - 1.117)	0.845* (0.703 - 1.017)	0.777 (0.390 - 1.547)	1.046 (0.569 - 1.924)	0.874 (0.395 - 1.935)	0.405*** (0.214 - 0.767)	0.641*** (0.481 - 0.854)	1.008 (0.730 - 1.393)	1.364** (1.005 - 1.850)
High School	0.973 (0.785 - 1.206)	1.141 (0.848 - 1.536)	0.726** (0.536 - 0.983)	0.805* (0.625 - 1.036)	0.419** (0.193 - 0.908)	1.363 (0.828 - 2.245)	0.875 (0.456 - 1.681)				
Some College	1.251** (1.008 - 1.553)	1.261 (0.930 - 1.711)	1.025 (0.759 - 1.384)	1.010 (0.785 - 1.299)	0.540 (0.257 - 1.135)	2.189*** (1.359 - 3.528)	0.877 (0.456 - 1.686)				
College Grad	1.067 (0.859 - 1.325)	1.061 (0.767 - 1.469)	0.882 (0.656 - 1.186)	0.915 (0.710 - 1.178)	0.463* (0.208 - 1.032)	1.954*** (1.196 - 3.192)	0.471** (0.242 - 0.918)				
Low Income	1.480*** (1.325 - 1.653)			1.700*** (1.516 - 1.908)	1.564** (1.028 - 2.380)	1.028 (0.730 - 1.446)	0.987 (0.700 - 1.391)	1.097 (0.736 - 1.634)	1.744*** (1.457 - 2.089)	1.422*** (1.180 - 1.713)	1.525*** (1.255 - 1.853)
Black	0.439*** (0.361 - 0.534)	0.457*** (0.341 - 0.614)	0.413*** (0.317 - 0.538)					0.956 (0.466 - 1.963)	0.384*** (0.267 - 0.551)	0.419*** (0.305 - 0.575)	0.392*** (0.277 - 0.555)
Hispanic	0.398*** (0.332 - 0.476)	0.302*** (0.231 - 0.396)	0.532*** (0.427 - 0.663)					0.232*** (0.143 - 0.376)	0.354*** (0.264 - 0.475)	0.556*** (0.406 - 0.762)	0.555*** (0.425 - 0.726)
Other	0.457*** (0.383 - 0.545)	0.400*** (0.305 - 0.524)	0.479*** (0.384 - 0.599)					0.574* (0.313 - 1.055)	0.637*** (0.475 - 0.856)	0.554*** (0.395 - 0.777)	0.313*** (0.227 - 0.432)

Married	0.550***	0.671***	0.511***	0.572***	0.585**	0.504***	0.388***	0.579***	0.558***	0.501***	0.596***
	(0.496 - 0.609)	(0.547 - 0.823)	(0.455 - 0.575)	(0.513 - 0.639)	(0.362 - 0.944)	(0.346 - 0.735)	(0.251 - 0.600)	(0.382 - 0.877)	(0.458 - 0.680)	(0.416 - 0.604)	(0.511 - 0.695)
Children	0.914*	0.897	0.930	0.926	0.986	0.841	0.998	0.882	0.972	0.843*	0.899
	(0.825 - 1.012)	(0.742 - 1.083)	(0.824 - 1.051)	(0.827 - 1.037)	(0.662 - 1.467)	(0.604 - 1.170)	(0.686 - 1.452)	(0.599 - 1.299)	(0.805 - 1.174)	(0.698 - 1.020)	(0.762 - 1.061)
Health Coverage	0.874*	0.914	0.804**	0.842**	0.670	0.959	0.906	0.954	0.715***	1.029	0.850
	(0.760 - 1.005)	(0.753 - 1.110)	(0.662 - 0.975)	(0.723 - 0.980)	(0.411 - 1.092)	(0.659 - 1.394)	(0.582 - 1.408)	(0.638 - 1.427)	(0.580 - 0.882)	(0.813 - 1.304)	(0.620 - 1.165)
Constant	0.205***	0.281***	0.260***	0.224***	0.207***	0.087***	0.193***	0.492**	0.220***	0.196***	0.146***
	(0.155 - 0.272)	(0.190 - 0.414)	(0.179 - 0.376)	(0.163 - 0.308)	(0.072 - 0.597)	(0.043 - 0.177)	(0.085 - 0.436)	(0.264 - 0.919)	(0.163 - 0.297)	(0.136 - 0.281)	(0.097 - 0.220)
Observations	406,391	379,666	405,513	405,421	289,070	304,346	327,815	315,688	391,165	393,953	399,432

Note: Referent group = No State Preemption of Labor Laws; Control variables include age, income, education, race, relationship status, children, health insurance coverage.
*** p<0.01, ** p<0.05.

Table A.4. Weighted Multivariate Logistic Regression Models of State Preemption Dimensions on Doctor Diagnosis of Depression for Men, by subgroups; Presented as Odds Ratios.

	Full Sample	Low Income	High Income	White	Black	Hispanic	Other	<High School	High School	Some College	College
Economic Preemption	1.073 (0.973 - 1.183)	1.164 (0.965 - 1.406)	1.029 (0.918 - 1.154)	1.057 (0.951 - 1.176)	0.834 (0.527 - 1.320)	1.036 (0.756 - 1.419)	1.059 (0.738 - 1.519)	0.735 (0.488 - 1.107)	1.201* (0.991 - 1.456)	1.097 (0.913 - 1.319)	1.000 (0.869 - 1.149)
Economic + Temporal Preemption	1.120** (1.003 - 1.251)	1.257** (1.014 - 1.559)	1.059 (0.931 - 1.204)	1.030 (0.916 - 1.157)	1.168 (0.717 - 1.902)	1.774** (1.116 - 2.820)	1.540** (1.024 - 2.316)	1.164 (0.688 - 1.972)	1.147 (0.939 - 1.402)	1.075 (0.879 - 1.314)	1.099 (0.937 - 1.288)
25-34	1.116 (0.964 - 1.293)	1.056 (0.846 - 1.317)	1.192* (0.974 - 1.458)	1.283*** (1.090 - 1.510)	1.458 (0.816 - 2.604)	0.656* (0.422 - 1.018)	0.877 (0.526 - 1.462)	0.763 (0.428 - 1.361)	1.057 (0.842 - 1.327)	1.287* (0.987 - 1.677)	1.648*** (1.242 - 2.185)
35-44	1.110 (0.941 - 1.311)	0.999 (0.748 - 1.333)	1.218* (0.982 - 1.512)	1.203** (1.005 - 1.439)	1.325 (0.681 - 2.579)	0.948 (0.562 - 1.598)	0.968 (0.523 - 1.790)	0.587* (0.322 - 1.073)	1.016 (0.769 - 1.343)	1.410** (1.045 - 1.902)	1.729*** (1.267 - 2.359)
45-54	0.886 (0.748 - 1.049)	0.784* (0.592 - 1.038)	0.985 (0.790 - 1.229)	0.992 (0.826 - 1.192)	1.070 (0.537 - 2.132)	0.639 (0.353 - 1.158)	0.875 (0.473 - 1.619)	0.510** (0.279 - 0.932)	0.762* (0.562 - 1.035)	1.023 (0.749 - 1.398)	1.547*** (1.142 - 2.094)
55-64	0.804** (0.676 - 0.955)	0.724** (0.529 - 0.990)	0.897 (0.719 - 1.117)	0.845* (0.703 - 1.016)	0.763 (0.382 - 1.525)	1.096 (0.603 - 1.992)	0.883 (0.399 - 1.956)	0.414*** (0.220 - 0.778)	0.641*** (0.481 - 0.854)	1.008 (0.730 - 1.392)	1.368** (1.008 - 1.856)
High School	0.973 (0.785 - 1.206)	1.138 (0.845 - 1.533)	0.726** (0.536 - 0.983)	0.805* (0.625 - 1.036)	0.411** (0.189 - 0.892)	1.383 (0.844 - 2.264)	0.877 (0.459 - 1.677)				
Some College	1.252** (1.008 - 1.553)	1.260 (0.929 - 1.710)	1.026 (0.761 - 1.385)	1.009 (0.784 - 1.299)	0.532* (0.253 - 1.117)	2.254*** (1.411 - 3.600)	0.889 (0.464 - 1.701)				
College Grad	1.067 (0.859 - 1.325)	1.060 (0.766 - 1.468)	0.883 (0.656 - 1.187)	0.914 (0.710 - 1.177)	0.459* (0.207 - 1.018)	2.005*** (1.236 - 3.252)	0.467** (0.241 - 0.905)				
Low Income	1.483*** (1.328 - 1.656)			1.702*** (1.517 - 1.909)	1.589** (1.056 - 2.393)	1.032 (0.735 - 1.450)	0.983 (0.697 - 1.386)	1.132 (0.764 - 1.676)	1.750*** (1.462 - 2.096)	1.423*** (1.181 - 1.715)	1.523*** (1.253 - 1.852)
Black	0.439*** (0.361 - 0.535)	0.459*** (0.342 - 0.616)	0.413*** (0.317 - 0.537)					0.983 (0.479 - 2.015)	0.384*** (0.268 - 0.551)	0.419*** (0.305 - 0.575)	0.392*** (0.277 - 0.556)
Hispanic	0.396*** (0.331 - 0.475)	0.298*** (0.227 - 0.392)	0.533*** (0.427 - 0.664)					0.233*** (0.144 - 0.376)	0.348*** (0.258 - 0.469)	0.551*** (0.402 - 0.755)	0.562*** (0.431 - 0.734)
Other	0.457*** (0.383 - 0.545)	0.398*** (0.304 - 0.522)	0.480*** (0.384 - 0.599)					0.573* (0.311 - 1.053)	0.635*** (0.473 - 0.853)	0.553*** (0.394 - 0.775)	0.314*** (0.228 - 0.434)
Married	0.550***	0.672***	0.511***	0.572***	0.588**	0.503***	0.381***	0.583**	0.558***	0.501***	0.595***

	(0.496 - 0.609)	(0.548 - 0.825)	(0.455 - 0.575)	(0.513 - 0.639)	(0.367 - 0.942)	(0.345 - 0.734)	(0.246 - 0.590)	(0.385 - 0.884)	(0.458 - 0.680)	(0.416 - 0.604)	(0.510 - 0.694)
Children	0.914*	0.896	0.930	0.927	0.982	0.846	1.015	0.877	0.976	0.844*	0.899
	(0.825 - 1.012)	(0.742 - 1.083)	(0.824 - 1.051)	(0.828 - 1.038)	(0.662 - 1.456)	(0.608 - 1.177)	(0.695 - 1.482)	(0.594 - 1.295)	(0.808 - 1.177)	(0.698 - 1.021)	(0.762 - 1.060)
Health Coverage	0.874*	0.913	0.804**	0.842**	0.668	0.960	0.893	0.945	0.716***	1.029	0.847
	(0.760 - 1.005)	(0.752 - 1.109)	(0.662 - 0.975)	(0.724 - 0.981)	(0.411 - 1.087)	(0.659 - 1.396)	(0.577 - 1.382)	(0.633 - 1.410)	(0.580 - 0.883)	(0.812 - 1.304)	(0.618 - 1.161)
Constant	0.205***	0.283***	0.259***	0.224***	0.210***	0.084***	0.195***	0.479**	0.220***	0.196***	0.146***
	(0.155 - 0.272)	(0.191 - 0.418)	(0.179 - 0.375)	(0.163 - 0.308)	(0.073 - 0.601)	(0.042 - 0.168)	(0.087 - 0.437)	(0.254 - 0.901)	(0.163 - 0.297)	(0.136 - 0.281)	(0.097 - 0.220)
Observations	406,391	379,666	405,513	405,421	289,070	304,346	327,815	315,688	391,165	393,953	399,432

Note: Referent group = No State Preemption of Labor Laws; Control variables include age, income, education, race, relationship status, children, health insurance coverage.
*** p<0.01, ** p<0.05.

Table A.5. Weighted Multivariate Logistic Regression Models for Number of State Preemption Laws on Continuous Measure of Self-rated Mental Health for Women, and by subgroups.

	Full Sample	Low Income	High Income	White	Black	Hispanic	Other	<High School	High School	Some College	College
1 Preemption	0.061	-0.084	0.079	-0.021	0.142	1.271	-1.436*	0.514	-0.117	-0.053	0.069
	(-0.507 - 0.628)	(-1.260 - 1.093)	(-0.542 - 0.701)	(-0.612 - 0.571)	(-1.725 - 2.009)	(-0.384 - 2.925)	(-3.073 - 0.201)	(-2.541 - 3.569)	(-1.544 - 1.310)	(-1.128 - 1.021)	(-0.611 - 0.748)
2+ Preemption	0.596***	0.433	0.555**	0.467**	-0.510	2.161***	0.017	2.632	0.584	0.471	0.277
	(0.174 - 1.018)	(-0.439 - 1.305)	(0.099 - 1.010)	(0.024 - 0.909)	(-1.773 - 0.753)	(0.566 - 3.756)	(-1.616 - 1.649)	(-0.032 - 5.296)	(-0.532 - 1.701)	(-0.312 - 1.253)	(-0.203 - 0.757)
25-34	-0.755*	-0.833	-0.828*	-1.086***	2.746**	-0.598	-3.060**	-2.480	-2.096**	-0.123	0.146
	(-1.518 - 0.009)	(-2.050 - 0.385)	(-1.775 - 0.119)	(-1.901 - - 0.271)	(0.486 - 5.007)	(-2.669 - 1.473)	(-5.698 - - 0.422)	(-6.313 - 1.352)	(-3.781 - - 0.411)	(-1.479 - 1.233)	(-0.769 - 1.060)
35-44	-1.177***	-1.315*	-1.153**	-1.349***	2.870**	-2.772**	-1.883	-3.026	-1.622*	-0.880	-0.150
	(-1.999 - - 0.355)	(-2.709 - 0.079)	(-2.143 - - 0.162)	(-2.189 - - 0.508)	(0.488 - 5.251)	(-5.081 - - 0.464)	(-5.142 - 1.377)	(-6.678 - 0.627)	(-3.521 - 0.276)	(-2.325 - 0.566)	(-1.127 - 0.826)
45-54	-1.285***	-0.449	-1.556***	-1.549***	1.308	-0.956	-1.986	-2.717	-1.093	-1.234*	-0.441
	(-2.050 - - 0.520)	(-1.739 - 0.841)	(-2.500 - - 0.612)	(-2.364 - - 0.733)	(-0.945 - 3.560)	(-3.269 - 1.357)	(-4.977 - 1.006)	(-6.521 - 1.087)	(-2.807 - 0.621)	(-2.527 - 0.059)	(-1.395 - 0.514)
55-64	-1.181***	-1.911***	-0.985*	-1.512***	1.581	-0.838	-1.922	-4.677**	-0.903	-1.409**	-0.053
	(-2.009 - - 0.352)	(-3.268 - - 0.554)	(-2.027 - 0.058)	(-2.368 - - 0.656)	(-0.930 - 4.092)	(-4.044 - 2.369)	(-5.773 - 1.929)	(-8.779 - - 0.575)	(-2.740 - 0.934)	(-2.746 - - 0.071)	(-1.152 - 1.047)
High School	-0.527	-0.471	-1.852	-2.446***	2.065	-1.189	1.113				
	(-1.816 - 0.762)	(-2.013 - 1.072)	(-4.163 - 0.459)	(-4.180 - - 0.713)	(-0.960 - 5.089)	(-3.578 - 1.200)	(-3.413 - 5.639)				
Some College	-1.418**	-1.200	-2.870**	-3.750***	2.297	-0.698	-1.881				
	(-2.660 - - 0.177)	(-2.692 - 0.293)	(-5.128 - - 0.613)	(-5.438 - - 2.062)	(-0.613 - 5.206)	(-3.009 - 1.613)	(-6.150 - 2.387)				
College Grad	-3.376***	-3.079***	-4.744***	-5.752***	0.465	-1.496	-4.099*				
	(-4.616 - - 2.136)	(-4.613 - - 1.544)	(-6.977 - - 2.511)	(-7.433 - - 4.071)	(-2.427 - 3.357)	(-3.904 - 0.911)	(-8.277 - 0.079)				
Low Income	1.371***			1.847***	1.974***	0.461	0.012	0.157	1.232**	1.622***	1.571***
	(0.875 - 1.867)			(1.295 - 2.399)	(0.607 - 3.341)	(-1.002 - 1.925)	(-1.596 - 1.620)	(-2.431 - 2.744)	(0.250 - 2.214)	(0.821 - 2.423)	(0.845 - 2.297)
Black	-0.487	-1.551**	-0.000					-6.001***	-1.578**	-0.126	0.427
	(-1.140 - 0.166)	(-2.792 - - 0.311)	(-0.724 - 0.723)					(-9.193 - - 2.809)	(-3.149 - - 0.006)	(-1.241 - 0.989)	(-0.425 - 1.278)
Hispanic	-0.815**	-2.677***	0.492					-3.541**	-2.851***	-0.587	1.291**
	(-1.585 - - 0.045)	(-3.800 - - 1.555)	(-0.525 - 1.509)					(-6.488 - - 0.595)	(-4.356 - - 1.346)	(-2.015 - 0.842)	(0.164 - 2.418)
Other	0.023	-1.282	0.534					-2.712	1.437	-0.345	0.042
	(-0.780 - 0.826)	(-2.957 - 0.393)	(-0.350 - 1.418)					(-7.005 - 1.582)	(-1.120 - 3.994)	(-1.813 - 1.122)	(-0.941 - 1.024)

Married	-1.742***	-1.625***	-1.679***	-1.780***	-1.463**	-0.870	-2.331***	-0.226	-2.035***	-1.591***	-1.854***
	(-2.152 - -1.332)	(-2.460 - -0.790)	(-2.140 - -1.218)	(-2.225 - -1.336)	(-2.771 - -0.154)	(-2.305 - 0.565)	(-3.734 - -0.928)	(-2.509 - 2.057)	(-3.101 - -0.970)	(-2.322 - -0.859)	(-2.370 - -1.338)
Children	0.342	0.609	0.259	0.285	0.158	1.391*	-0.455	0.603	0.823	0.193	0.257
	(-0.098 - 0.782)	(-0.298 - 1.516)	(-0.221 - 0.740)	(-0.167 - 0.737)	(-1.142 - 1.458)	(-0.019 - 2.801)	(-2.281 - 1.370)	(-1.855 - 3.060)	(-0.340 - 1.985)	(-0.645 - 1.031)	(-0.280 - 0.794)
Health Coverage	-1.130***	-0.938*	-1.735***	-2.314***	-1.723	0.420	0.383	-0.606	-1.618**	-1.006	-1.601**
	(-1.941 - -0.320)	(-1.977 - 0.102)	(-2.945 - -0.525)	(-3.253 - -1.376)	(-3.907 - 0.462)	(-1.292 - 2.133)	(-2.095 - 2.861)	(-3.017 - 1.804)	(-3.077 - -0.158)	(-2.271 - 0.258)	(-3.085 - -0.117)
Constant	13.788***	15.498***	15.554***	17.315***	7.928***	10.269***	15.280***	16.354***	14.472***	11.966***	9.876***
	(12.222 - 15.353)	(13.593 - 17.404)	(13.039 - 18.069)	(15.361 - 19.269)	(3.879 - 11.976)	(7.010 - 13.529)	(10.248 - 20.313)	(11.854 - 20.854)	(12.452 - 16.491)	(10.270 - 13.662)	(8.158 - 11.594)
Observations	370,916	372,444	375,690	376,786	247,721	264,619	273,929	223,506	364,643	373,273	378,888

Note: Referent group = No State Preemption of Labor Laws; Control variables include age, income, education, race, relationship status, children, health insurance coverage.
*** p<0.01, ** p<0.05

Table A.6. Weighted Multivariate Logistic Regression Models for Dimensions of State Preemption Laws on Continuous Measure of Self-rated Mental Health for Women, and by subgroups.

	Full Sample	**Low Income**	**High Income**	**White**	**Black**	**Hispanic**	**Other**	**<High School**	**High School**	**Some College**	**College**
Economic Preemption	0.220 (-0.221 - 0.662)	-0.025 (-0.928 - 0.879)	0.259 (-0.223 - 0.741)	0.095 (-0.370 - 0.560)	-0.290 (-1.651 - 1.070)	1.467** (0.082 - 2.853)	-0.909 (-2.367 - 0.548)	1.073 (-1.477 - 3.623)	0.250 (-0.898 - 1.398)	-0.060 (-0.889 - 0.769)	0.171 (-0.347 - 0.690)
Economic + Temporal Preemption	0.816*** (0.329 - 1.303)	0.873 (-0.148 - 1.895)	0.655** (0.133 - 1.177)	0.720*** (0.202 - 1.238)	-0.366 (-1.871 - 1.139)	2.819*** (0.680 - 4.958)	0.491 (-1.647 - 2.630)	3.440** (0.540 - 6.340)	0.452 (-0.857 - 1.761)	1.066** (0.196 - 1.937)	0.258 (-0.287 - 0.803)
25-34	-0.755* (-1.519 - 0.010)	-0.844 (-2.066 - 0.378)	-0.839* (-1.794 - 0.117)	-1.079*** (-1.893 - -0.265)	2.706** (0.456 - 4.956)	-0.674 (-2.748 - 1.400)	-3.024** (-5.667 - -0.381)	-2.473 (-6.221 - 1.274)	-2.070** (-3.771 - -0.369)	-0.124 (-1.489 - 1.242)	0.141 (-0.770 - 1.052)
35-44	-1.165*** (-1.988 - -0.342)	-1.280* (-2.676 - 0.116)	-1.157** (-2.152 - -0.163)	-1.339*** (-2.178 - -0.500)	2.807** (0.429 - 5.184)	-2.740** (-5.045 - -0.436)	-1.823 (-5.087 - 1.441)	-2.977 (-6.530 - 0.575)	-1.595 (-3.509 - 0.318)	-0.877 (-2.321 - 0.566)	-0.153 (-1.126 - 0.821)
45-54	-1.284*** (-2.049 - -0.518)	-0.428 (-1.718 - 0.862)	-1.568*** (-2.516 - -0.620)	-1.544*** (-2.357 - -0.730)	1.274 (-0.969 - 3.516)	-0.982 (-3.292 - 1.329)	-1.995 (-4.986 - 0.996)	-2.747 (-6.415 - 0.922)	-1.085 (-2.807 - 0.637)	-1.231* (-2.527 - 0.066)	-0.447 (-1.398 - 0.503)
55-64	-1.179*** (-2.009 - -0.350)	-1.886*** (-3.240 - -0.531)	-0.996* (-2.045 - 0.053)	-1.506*** (-2.361 - -0.651)	1.557 (-0.949 - 4.063)	-0.837 (-4.089 - 2.414)	-1.882 (-5.736 - 1.972)	-4.593** (-8.541 - -0.646)	-0.927 (-2.762 - 0.909)	-1.410** (-2.753 - -0.067)	-0.053 (-1.151 - 1.046)
High School	-0.529 (-1.818 - 0.761)	-0.465 (-2.012 - 1.082)	-1.836 (-4.153 - 0.480)	-2.450*** (-4.181 - -0.718)	2.093 (-0.908 - 5.094)	-1.185 (-3.570 - 1.201)	1.038 (-3.538 - 5.614)				
Some College	-1.406** (-2.647 - -0.165)	-1.191 (-2.683 - 0.301)	-2.839** (-5.102 - -0.577)	-3.745*** (-5.432 - -2.058)	2.292 (-0.580 - 5.163)	-0.665 (-2.949 - 1.620)	-1.871 (-6.203 - 2.462)				
College Grad	-3.371*** (-4.612 - -2.131)	-3.059*** (-4.599 - -1.519)	-4.723*** (-6.961 - -2.485)	-5.747*** (-7.427 - -4.067)	0.477 (-2.380 - 3.333)	-1.453 (-3.853 - 0.948)	-4.246** (-8.479 - -0.013)				
Low Income	1.381*** (0.886 - 1.877)			1.853*** (1.300 - 2.407)	1.925*** (0.578 - 3.273)	0.449 (-1.009 - 1.907)	0.014 (-1.594 - 1.623)	0.380 (-2.152 - 2.913)	1.260** (0.283 - 2.237)	1.605*** (0.806 - 2.405)	1.577*** (0.849 - 2.304)
Black	-0.478 (-1.131 - 0.175)	-1.526** (-2.761 - -0.292)	0.004 (-0.721 - 0.728)					-6.079*** (-9.232 - -2.927)	-1.579* (-3.158 - 0.001)	-0.109 (-1.218 - 0.999)	0.431 (-0.420 - 1.283)
Hispanic	-0.819** (-1.588 - -0.050)	-2.651*** (-3.775 - -1.526)	0.484 (-0.533 - 1.500)					-3.718*** (-6.463 - -0.973)	-2.970*** (-4.491 - -1.448)	-0.525 (-1.939 - 0.890)	1.276** (0.146 - 2.406)
Other	0.030 (-0.774 - 0.834)	-1.249 (-2.925 - 0.427)	0.533 (-0.351 - 1.418)					-2.654 (-7.064 - 1.757)	1.403 (-1.161 - 3.966)	-0.288 (-1.757 - 1.182)	0.029 (-0.954 - 1.012)

Married	-1.737***	-1.634***	-1.671***	-1.783***	-1.480**	-0.846	-2.314***	-0.170	-1.996***	-1.583***	-1.855***
	(-2.146 - -1.327)	(-2.469 - -0.798)	(-2.131 - -1.210)	(-2.227 - -1.339)	(-2.803 - -0.157)	(-2.267 - 0.575)	(-3.716 - -0.912)	(-2.455 - 2.114)	(-3.061 - -0.930)	(-2.313 - -0.854)	(-2.370 - -1.339)
Children	0.333	0.576	0.261	0.276	0.182	1.388*	-0.476	0.527	0.832	0.186	0.258
	(-0.108 - 0.774)	(-0.337 - 1.490)	(-0.221 - 0.742)	(-0.175 - 0.728)	(-1.125 - 1.488)	(-0.019 - 2.795)	(-2.302 - 1.349)	(-1.865 - 2.920)	(-0.332 - 1.996)	(-0.651 - 1.024)	(-0.279 - 0.795)
Health Coverage	-1.129***	-0.950*	-1.734***	-2.333***	-1.725	0.464	0.559	-0.645	-1.619**	-1.030	-1.595**
	(-1.941 - -0.316)	(-1.994 - 0.094)	(-2.946 - -0.522)	(-3.269 - -1.397)	(-3.890 - 0.440)	(-1.248 - 2.175)	(-1.889 - 3.007)	(-3.046 - 1.757)	(-3.079 - -0.160)	(-2.297 - 0.237)	(-3.083 - -0.107)
Constant	13.775***	15.495***	15.534***	17.327***	7.966***	10.234***	15.177***	16.327***	14.460***	11.975***	9.876***
	(12.215 - 15.336)	(13.600 - 17.389)	(13.020 - 18.048)	(15.379 - 19.276)	(3.944 - 11.988)	(7.016 - 13.451)	(10.105 - 20.249)	(11.899 - 20.755)	(12.441 - 16.480)	(10.284 - 13.666)	(8.158 - 11.595)
Observations	370,916	372,444	375,690	376,786	247,721	264,619	273,929	223,506	364,643	373,273	378,888

Note: Referent group = No State Preemption of Labor Laws; Control variables include age, income, education, race, relationship status, children, health insurance coverage.
*** $p<0.01$, ** $p<0.05$.

Table A.7. Weighted Multivariate Logistic Regression Models for Number of State Preemption Laws on Continuous Measure of Self-rated Mental Health for Men, and by subgroups; Presented as Odds Ratios.

	Full Sample	Low Income	High Income	White	Black	Hispanic	Other	<High School	High School	Some College	College
1 Preemption	0.158	0.411	0.034	0.075	-0.278	0.662	-1.715*	-0.258	0.983	-0.217	0.158
	(-0.473 - 0.789)	(-0.880 - 1.703)	(-0.667 - 0.734)	(-0.614 - 0.764)	(-2.647 - 2.092)	(-0.972 - 2.295)	(-3.523 - 0.094)	(-2.993 - 2.476)	(-0.289 - 2.254)	(-1.393 - 0.959)	(-0.473 - 0.789)
2+ Preemption	0.560**	0.170	0.629**	0.355	1.606	0.239	0.174	-0.002	0.337	0.809	0.560**
	(0.081 - 1.038)	(-0.818 - 1.159)	(0.090 - 1.168)	(-0.155 - 0.864)	(-0.313 - 3.526)	(-1.286 - 1.763)	(-1.613 - 1.962)	(-2.087 - 2.084)	(-0.625 - 1.299)	(-0.065 - 1.683)	(0.081 - 1.038)
25-34	0.958***	1.303**	0.768*	1.320***	1.197	0.615	-0.682	0.468	0.986	1.173**	0.958***
	(0.266 - 1.650)	(0.146 - 2.461)	(-0.103 - 1.639)	(0.552 - 2.089)	(-1.362 - 3.756)	(-1.314 - 2.544)	(-2.875 - 1.511)	(-2.636 - 3.572)	(-0.277 - 2.250)	(0.031 - 2.314)	(0.266 - 1.650)
35-44	0.874**	0.801	0.930*	1.252***	1.460	-0.110	1.121	0.779	0.172	0.842	0.874**
	(0.079 - 1.669)	(-0.542 - 2.144)	(-0.053 - 1.913)	(0.373 - 2.132)	(-1.435 - 4.355)	(-2.151 - 1.931)	(-1.755 - 3.998)	(-2.220 - 3.778)	(-1.235 - 1.579)	(-0.496 - 2.180)	(0.079 - 1.669)
45-54	0.090	-0.063	0.190	0.682	0.052	-0.527	0.023	-1.068	-0.663	0.395	0.090
	(-0.698 - 0.877)	(-1.475 - 1.350)	(-0.782 - 1.162)	(-0.192 - 1.555)	(-2.791 - 2.895)	(-2.802 - 1.747)	(-2.798 - 2.845)	(-4.349 - 2.214)	(-2.143 - 0.818)	(-0.922 - 1.712)	(-0.698 - 0.877)
55-64	0.242	0.004	0.414	0.574	0.087	1.216	-0.066	0.318	-1.781**	1.460	0.242
	(-0.667 - 1.151)	(-1.818 - 1.825)	(-0.667 - 1.494)	(-0.436 - 1.583)	(-2.993 - 3.166)	(-1.753 - 4.184)	(-2.948 - 2.815)	(-2.999 - 3.634)	(-3.263 - - 0.299)	(-0.382 - 3.301)	(-0.667 - 1.151)
High School	-1.273**	-0.415	-3.069***	-3.238***	-3.669*	0.773	-3.404				-1.273**
	(-2.451 - - 0.095)	(-1.851 - 1.022)	(-4.970 - - 1.168)	(-4.970 - - 1.506)	(-7.719 - 0.381)	(-0.987 - 2.532)	(-8.013 - 1.205)				(-2.451 - - 0.095)
Some College	-2.472***	-0.678	-4.636***	-4.733***	-4.870**	1.154	-5.261**				-2.472***
	(-3.663 - - 1.281)	(-2.266 - 0.909)	(-6.499 - - 2.773)	(-6.452 - - 3.014)	(-8.895 - - 0.846)	(-0.884 - 3.192)	(-9.734 - - 0.789)				(-3.663 - - 1.281)
College Grad	-4.349***	-2.904***	-6.172***	-6.766***	-5.409**	-0.486	-5.345**				-4.349***
	(-5.536 - - 3.161)	(-4.603 - - 1.204)	(-8.020 - - 4.323)	(-8.473 - - 5.058)	(-9.554 - - 1.265)	(-2.498 - 1.526)	(-9.716 - - 0.974)				(-5.536 - - 3.161)
Low Income	0.876***			1.447***	1.027	-0.302	1.394*	-1.135	0.415	1.973***	0.876***
	(0.276 - 1.477)			(0.760 - 2.133)	(-0.953 - 3.006)	(-1.888 - 1.283)	(-0.258 - 3.046)	(-3.234 - 0.963)	(-0.569 - 1.400)	(0.972 - 2.974)	(0.276 - 1.477)
Black	0.504	-0.115	0.695					0.477	-0.070	0.072	0.504
	(-0.403 - 1.411)	(-1.660 - 1.431)	(-0.399 - 1.788)					(-3.613 - 4.566)	(-1.737 - 1.597)	(-1.388 - 1.533)	(-0.403 - 1.411)
Hispanic	-1.391***	-2.994***	-0.190					-5.935***	-2.220***	0.238	-1.391***
	(-2.169 - - 0.612)	(-4.221 - - 1.767)	(-1.183 - 0.803)					(-8.208 - - 3.662)	(-3.532 - - 0.908)	(-1.217 - 1.692)	(-2.169 - - 0.612)
Other	-0.231	-0.790	-0.107					-0.578	-0.581	-0.823	-0.231
	(-1.073 - 0.611)	(-2.484 - 0.904)	(-1.085 - 0.871)					(-5.341 - 4.184)	(-2.352 - 1.191)	(-2.147 - 0.502)	(-1.073 - 0.611)

Married	-1.299***	-0.157	-1.638***	-1.434***	0.009	-1.029	-2.366**	-0.981	-0.592	-0.960*	-1.299***
	(-1.845 - -0.753)	(-1.303 - 0.988)	(-2.249 - -1.027)	(-2.025 - -0.842)	(-2.077 - 2.096)	(-2.658 - 0.601)	(-4.168 - -0.564)	(-3.217 - 1.255)	(-1.588 - 0.404)	(-2.010 - 0.089)	(-1.845 - -0.753)
Children	-0.306	-0.236	-0.270	-0.333	-0.315	-0.069	0.385	-0.419	-0.907*	-0.117	-0.306
	(-0.813 - 0.201)	(-1.224 - 0.751)	(-0.858 - 0.317)	(-0.894 - 0.228)	(-2.103 - 1.474)	(-1.470 - 1.332)	(-1.318 - 2.089)	(-2.317 - 1.479)	(-1.856 - 0.042)	(-1.065 - 0.831)	(-0.813 - 0.201)
Health Coverage	-1.079***	-1.145**	-1.155*	-1.561***	-0.693	-1.158	-0.502	-1.293	-1.933***	-0.675	-1.079***
	(-1.892 - -0.267)	(-2.203 - -0.088)	(-2.367 - 0.056)	(-2.557 - -0.566)	(-3.162 - 1.777)	(-2.917 - 0.601)	(-2.713 - 1.709)	(-3.476 - 0.890)	(-3.231 - -0.635)	(-1.995 - 0.644)	(-1.892 - -0.267)
Constant	12.673***	12.746***	14.587***	14.937***	13.673***	9.565***	14.570***	16.624***	12.841***	8.940***	12.673***
	(11.144 - 14.203)	(10.721 - 14.771)	(12.329 - 16.844)	(12.875 - 16.999)	(9.082 - 18.264)	(6.493 - 12.637)	(9.167 - 19.972)	(12.943 - 20.306)	(11.021 - 14.662)	(7.235 - 10.645)	(11.144 - 14.203)
Observations	351,116	335,048	354,075	357,567	219,503	238,405	259,745	240,438	343,162	344,524	351,116

Note: Referent group = No State Preemption of Labor Laws; Control variables include age, income, education, race, relationship status, children, health insurance coverage.
*** $p<0.01$, ** $p<0.05$.

Table A.8. Weighted Multivariate Logistic Regression Models for Dimensions of State Preemption Laws on Continuous Measure of Self-rated Mental Health for Men, and by subgroups; Presented as Odds Ratios.

	Full Sample	Low Income	High Income	White	Black	Hispanic	Other	<High School	High School	Some College	College
Economic Preemption	0.220 (-0.221 - 0.662)	-0.025 (-0.928 - 0.879)	0.259 (-0.223 - 0.741)	0.095 (-0.370 - 0.560)	-0.290 (-1.651 - 1.070)	1.467** (0.082 - 2.853)	-0.909 (-2.367 - 0.548)	1.073 (-1.477 - 3.623)	0.250 (-0.898 - 1.398)	-0.060 (-0.889 - 0.769)	0.171 (-0.347 - 0.690)
Economic + Temporal Preemption	0.816*** (0.329 - 1.303)	0.873 (-0.148 - 1.895)	0.655** (0.133 - 1.177)	0.720*** (0.202 - 1.238)	-0.366 (-1.871 - 1.139)	2.819*** (0.680 - 4.958)	0.491 (-1.647 - 2.630)	3.440** (0.540 - 6.340)	0.452 (-0.857 - 1.761)	1.066** (0.196 - 1.937)	0.258 (-0.287 - 0.803)
25-34	-0.755* (-1.519 - 0.010)	-0.844 (-2.066 - 0.378)	-0.839* (-1.794 - 0.117)	-1.079*** (-1.893 - -0.265)	2.706** (0.456 - 4.956)	-0.674 (-2.748 - 1.400)	-3.024** (-5.667 - -0.381)	-2.473 (-6.221 - 1.274)	-2.070** (-3.771 - -0.369)	-0.124 (-1.489 - 1.242)	0.141 (-0.770 - 1.052)
35-44	-1.165*** (-1.988 - -0.342)	-1.280* (-2.676 - 0.116)	-1.157** (-2.152 - -0.163)	-1.339*** (-2.178 - -0.500)	2.807** (0.429 - 5.184)	-2.740** (-5.045 - -0.436)	-1.823 (-5.087 - 1.441)	-2.977 (-6.530 - 0.575)	-1.595 (-3.509 - 0.318)	-0.877 (-2.321 - 0.566)	-0.153 (-1.126 - 0.821)
45-54	-1.284*** (-2.049 - -0.518)	-0.428 (-1.718 - 0.862)	-1.568*** (-2.516 - -0.620)	-1.544*** (-2.357 - -0.730)	1.274 (-0.969 - 3.516)	-0.982 (-3.292 - 1.329)	-1.995 (-4.986 - 0.996)	-2.747 (-6.415 - 0.922)	-1.085 (-2.807 - 0.637)	-1.231* (-2.527 - 0.066)	-0.447 (-1.398 - 0.503)
55-64	-1.179*** (-2.009 - -0.350)	-1.886*** (-3.240 - -0.531)	-0.996* (-2.045 - 0.053)	-1.506*** (-2.361 - -0.651)	1.557 (-0.949 - 4.063)	-0.837 (-4.089 - 2.414)	-1.882 (-5.736 - 1.972)	-4.593** (-8.541 - -0.646)	-0.927 (-2.762 - 0.909)	-1.410** (-2.753 - -0.067)	-0.053 (-1.151 - 1.046)
High School	-0.529 (-1.818 - 0.761)	-0.465 (-2.012 - 1.082)	-1.836 (-4.153 - 0.480)	-2.450*** (-4.181 - -0.718)	2.093 (-0.908 - 5.094)	-1.185 (-3.570 - 1.201)	1.038 (-3.538 - 5.614)				
Some College	-1.406** (-2.647 - -0.165)	-1.191 (-2.683 - 0.301)	-2.839** (-5.102 - -0.577)	-3.745*** (-5.432 - -2.058)	2.292 (-0.580 - 5.163)	-0.665 (-2.949 - 1.620)	-1.871 (-6.203 - 2.462)				
College Grad	-3.371*** (-4.612 - -2.131)	-3.059*** (-4.599 - -1.519)	-4.723*** (-6.961 - -2.485)	-5.747*** (-7.427 - -4.067)	0.477 (-2.380 - 3.333)	-1.453 (-3.853 - 0.948)	-4.246** (-8.479 - -0.013)				
Low Income	1.381*** (0.886 - 1.877)			1.853*** (1.300 - 2.407)	1.925*** (0.578 - 3.273)	0.449 (-1.009 - 1.907)	0.014 (-1.594 - 1.623)	0.380 (-2.152 - 2.913)	1.260** (0.283 - 2.237)	1.605*** (0.806 - 2.405)	1.577*** (0.849 - 2.304)
Black	-0.478 (-1.131 - 0.175)	-1.526** (-2.761 - -0.292)	0.004 (-0.721 - 0.728)					-6.079*** (-9.232 - -2.927)	-1.579* (-3.158 - 0.001)	-0.109 (-1.218 - 0.999)	0.431 (-0.420 - 1.283)
Hispanic	-0.819** (-1.588 - -0.050)	-2.651*** (-3.775 - -1.526)	0.484 (-0.533 - 1.500)					-3.718*** (-6.463 - -0.973)	-2.970*** (-4.491 - -1.448)	-0.525 (-1.939 - 0.890)	1.276** (0.146 - 2.406)
Other	0.030 (-0.774 - 0.834)	-1.249 (-2.925 - 0.427)	0.533 (-0.351 - 1.418)					-2.654 (-7.064 - 1.757)	1.403 (-1.161 - 3.966)	-0.288 (-1.757 - 1.182)	0.029 (-0.954 - 1.012)

Married	-1.737***	-1.634***	-1.671***	-1.783***	-1.480**	-0.846	-2.314***	-0.170	-1.996***	-1.583***	-1.855***
	(-2.146 - -1.327)	(-2.469 - -0.798)	(-2.131 - -1.210)	(-2.227 - -1.339)	(-2.803 - -0.157)	(-2.267 - 0.575)	(-3.716 - -0.912)	(-2.455 - 2.114)	(-3.061 - -0.930)	(-2.313 - -0.854)	(-2.370 - -1.339)
Children	0.333	0.576	0.261	0.276	0.182	1.388*	-0.476	0.527	0.832	0.186	0.258
	(-0.108 - 0.774)	(-0.337 - 1.490)	(-0.221 - 0.742)	(-0.175 - 0.728)	(-1.125 - 1.488)	(-0.019 - 2.795)	(-2.302 - 1.349)	(-1.865 - 2.920)	(-0.332 - 1.996)	(-0.651 - 1.024)	(-0.279 - 0.795)
Health Coverage	-1.129***	-0.950*	-1.734***	-2.333***	-1.725	0.464	0.559	-0.645	-1.619**	-1.030	-1.595**
	(-1.941 - -0.316)	(-1.994 - 0.094)	(-2.946 - -0.522)	(-3.269 - -1.397)	(-3.890 - 0.440)	(-1.248 - 2.175)	(-1.889 - 3.007)	(-3.046 - 1.757)	(-3.079 - -0.160)	(-2.297 - 0.237)	(-3.083 - -0.107)
Constant	13.775***	15.495***	15.534***	17.327***	7.966***	10.234***	15.177***	16.327***	14.460***	11.975***	9.876***
	(12.215 - 15.336)	(13.600 - 17.389)	(13.020 - 18.048)	(15.379 - 19.276)	(3.944 - 11.988)	(7.016 - 13.451)	(10.105 - 20.249)	(11.899 - 20.755)	(12.441 - 16.480)	(10.284 - 13.666)	(8.158 - 11.595)
Observations	370,916	372,444	375,690	376,786	247,721	264,619	273,929	223,506	364,643	373,273	378,888

Note: Referent group = No State Preemption of Labor Laws; Control variables include age, income, education, race, relationship status, children, health insurance coverage.
*** p<0.01, ** p<0.05.

Table A.9. Fully Controlled Weighted Multivariate Logistic Regression Models for Number of State Preemption Laws on Self-rated Mental Health for Women, and by subgroups; Presented as Odds Ratios.

	Full Sample	Low Income	High Income	White	Black	Hispanic	Other	<High School	High School	Some College	College
1 Preemption	0.236 (-0.260 - 0.731)	0.168 (-0.842 - 1.177)	0.239 (-0.319 - 0.797)	0.065 (-0.465 - 0.595)	0.579 (-1.371 - 2.528)	0.540 (-0.839 - 1.920)	-0.680 (-2.389 - 1.030)	-0.063 (-2.114 - 1.987)	0.254 (-0.751 - 1.258)	0.271 (-0.655 - 1.196)	-0.086 (-0.711 - 0.539)
2+ Preemption	0.823*** (0.262 - 1.383)	0.539 (-0.628 - 1.705)	0.793** (0.164 - 1.421)	0.660** (0.062 - 1.258)	1.704 (-0.554 - 3.961)	0.189 (-1.889 - 2.268)	-0.128 (-2.023 - 1.766)	-0.210 (-2.931 - 2.510)	1.228** (0.091 - 2.365)	0.725 (-0.308 - 1.757)	0.344 (-0.333 - 1.021)
25-34	0.964*** (0.273 - 1.656)	1.303** (0.151 - 2.455)	0.761* (-0.108 - 1.629)	1.325*** (0.556 - 2.093)	1.258 (-1.303 - 3.819)	0.596 (-1.346 - 2.538)	-0.627 (-2.827 - 1.574)	0.449 (-2.658 - 3.557)	0.986 (-0.281 - 2.254)	1.184** (0.041 - 2.327)	1.546*** (0.614 - 2.478)
35-44	0.883** (0.088 - 1.678)	0.795 (-0.547 - 2.138)	0.934* (-0.046 - 1.914)	1.257*** (0.378 - 2.135)	1.447 (-1.426 - 4.319)	-0.140 (-2.220 - 1.939)	1.209 (-1.687 - 4.104)	0.804 (-2.200 - 3.809)	0.196 (-1.211 - 1.604)	0.845 (-0.490 - 2.181)	2.363*** (1.130 - 3.596)
45-54	0.093 (-0.695 - 0.881)	-0.068 (-1.485 - 1.348)	0.187 (-0.784 - 1.158)	0.679 (-0.195 - 1.552)	0.023 (-2.858 - 2.905)	-0.567 (-2.883 - 1.750)	-0.110 (-2.979 - 2.759)	-1.045 (-4.331 - 2.241)	-0.695 (-2.180 - 0.791)	0.361 (-0.970 - 1.692)	1.809*** (0.694 - 2.924)
55-64	0.237 (-0.672 - 1.147)	0.023 (-1.789 - 1.835)	0.399 (-0.680 - 1.478)	0.560 (-0.451 - 1.572)	0.098 (-2.961 - 3.157)	1.179 (-1.812 - 4.170)	-0.107 (-3.002 - 2.788)	0.339 (-2.943 - 3.620)	-1.741** (-3.219 - -0.263)	1.451 (-0.400 - 3.302)	1.571*** (0.453 - 2.689)
High School	-1.279** (-2.456 - -0.102)	-0.430 (-1.870 - 1.010)	-3.060*** (-4.958 - -1.162)	-3.232*** (-4.966 - -1.499)	-3.664* (-7.708 - 0.380)	0.784 (-0.976 - 2.544)	-3.320 (-7.973 - 1.332)				
Some College	-2.479*** (-3.668 - -1.289)	-0.677 (-2.269 - 0.914)	-4.630*** (-6.491 - -2.770)	-4.718*** (-6.437 - -3.000)	-4.917** (-8.955 - -0.879)	1.182 (-0.845 - 3.210)	-5.235** (-9.782 - -0.688)				
College Grad	-4.355*** (-5.539 - -3.170)	-2.914*** (-4.612 - -1.216)	-6.174*** (-8.018 - -4.330)	-6.754*** (-8.460 - -5.048)	-5.423** (-9.593 - -1.253)	-0.464 (-2.458 - 1.529)	-5.415** (-9.865 - -0.964)				
Low Income	0.884*** (0.283 - 1.484)			1.444*** (0.759 - 2.130)	1.146 (-0.794 - 3.086)	-0.310 (-1.901 - 1.281)	1.375 (-0.281 - 3.030)	-1.159 (-3.301 - 0.984)	0.401 (-0.590 - 1.392)	1.968*** (0.965 - 2.970)	1.516*** (0.519 - 2.512)
Black	0.497 (-0.408 - 1.403)	-0.096 (-1.643 - 1.452)	0.676 (-0.414 - 1.766)					0.474 (-3.613 - 4.562)	-0.056 (-1.722 - 1.610)	0.069 (-1.393 - 1.532)	1.779** (0.338 - 3.220)
Hispanic	-1.387*** (-2.163 - -0.611)	-2.901*** (-4.123 - -1.679)	-0.223 (-1.213 - 0.767)					-5.975*** (-8.206 - -3.744)	-1.983*** (-3.320 - -0.646)	0.093 (-1.364 - 1.550)	0.605 (-0.618 - 1.829)
Other	-0.216 (-1.058 - 0.627)	-0.765 (-2.458 - 0.928)	-0.095 (-1.075 - 0.885)					-0.615 (-5.404 - 4.174)	-0.564 (-2.342 - 1.213)	-0.811 (-2.153 - 0.531)	0.465 (-0.794 - 1.723)
Married	-1.294***	-0.163	-1.629***	-1.430***	0.091	-1.017	-2.351**	-0.992	-0.613	-0.962*	-2.295***

	(-1.839 - -0.750)	(-1.309 - 0.983)	(-2.239 - -1.020)	(-2.019 - -0.840)	(-1.983 - 2.165)	(-2.652 - 0.617)	(-4.168 - -0.533)	(-3.233 - 1.248)	(-1.608 - 0.382)	(-2.014 - 0.090)	(-3.018 - -1.573)
Children	-0.316	-0.258	-0.277	-0.349	-0.243	-0.074	0.414	-0.435	-0.966**	-0.106	0.179
	(-0.823 - 0.190)	(-1.248 - 0.731)	(-0.865 - 0.310)	(-0.911 - 0.214)	(-2.027 - 1.541)	(-1.481 - 1.334)	(-1.306 - 2.133)	(-2.364 - 1.495)	(-1.915 - -0.017)	(-1.055 - 0.842)	(-0.569 - 0.928)
Health Coverage	-1.068**	-1.146**	-1.148*	-1.561***	-0.676	-1.189	-0.588	-1.276	-1.935***	-0.663	-0.778
	(-1.881 - -0.255)	(-2.203 - -0.088)	(-2.360 - 0.063)	(-2.557 - -0.565)	(-3.202 - 1.849)	(-2.952 - 0.574)	(-2.810 - 1.635)	(-3.471 - 0.918)	(-3.241 - -0.629)	(-1.990 - 0.663)	(-2.196 - 0.640)
Constant	12.663***	12.722***	14.584***	14.929***	13.591***	9.596***	14.625***	16.662***	12.812***	8.958***	7.119***
	(11.136 - 14.190)	(10.691 - 14.752)	(12.339 - 16.829)	(12.866 - 16.993)	(8.970 - 18.213)	(6.496 - 12.695)	(9.112 - 20.137)	(12.945 - 20.378)	(10.980 - 14.643)	(7.250 - 10.667)	(5.462 - 8.775)
Observations	351,116	335,048	354,075	357,567	219,503	238,405	259,745	240,438	343,162	344,524	353,550

Note: Referent group = No State Preemption of Labor Laws; Control variables include age, income, education, race, relationship status, children, health insurance coverage.
*** $p<0.01$, ** $p<0.05$.

Table A.10. Fully Controlled Weighted Multivariate Logistic Regression Models for Dimensions of State Preemption Laws on Self-rated Mental Health for Women, and by subgroups; Presented as Odds Ratios.

	Full Sample	Low Income	High Income	White	Black	Hispanic	Other	<High School	High School	Some College	College
Temporal	1.024 (0.922 - 1.137)	1.057 (0.893 - 1.251)	0.986 (0.866 - 1.122)	0.94 (0.836 - 1.056)	0.865 (0.649 - 1.152)	1.396** (1.040 - 1.874)	1.014 (0.706 - 1.457)	1.179 (0.752 - 1.849)	1.081 (0.870 - 1.342)	0.897 (0.746 - 1.078)	1.045 (0.897 - 1.217)
Economic + Temporal	1.190*** (1.063 - 1.332)	1.213** (1.010 - 1.456)	1.144* (0.995 - 1.315)	1.096 (0.968 - 1.242)	1.023 (0.753 - 1.391)	1.941*** (1.202 - 3.134)	0.95 (0.601 - 1.501)	1.861* (0.984 - 3.520)	1.176 (0.932 - 1.485)	1.147 (0.954 - 1.379)	1.078 (0.916 - 1.268)
25-34	0.691*** (0.588 - 0.811)	0.689*** (0.554 - 0.858)	0.674*** (0.533 - 0.852)	0.664*** (0.551 - 0.801)	1.323 (0.859 - 2.038)	0.704 (0.454 - 1.091)	0.394*** (0.229 - 0.678)	0.304*** (0.152 - 0.608)	0.574*** (0.426 - 0.773)	0.895 (0.682 - 1.174)	0.798* (0.611 - 1.041)
35-44	0.542*** (0.457 - 0.644)	0.544*** (0.429 - 0.691)	0.534*** (0.417 - 0.683)	0.545*** (0.446 - 0.667)	0.988 (0.622 - 1.568)	0.406*** (0.255 - 0.647)	0.504** (0.263 - 0.965)	0.272*** (0.148 - 0.501)	0.571*** (0.412 - 0.790)	0.586*** (0.444 - 0.774)	0.679*** (0.507 - 0.909)
45-54	0.456*** (0.387 - 0.538)	0.564*** (0.449 - 0.710)	0.411*** (0.325 - 0.519)	0.471*** (0.389 - 0.571)	0.69 (0.423 - 1.126)	0.474*** (0.299 - 0.754)	0.280*** (0.157 - 0.500)	0.268*** (0.143 - 0.501)	0.527*** (0.388 - 0.715)	0.477*** (0.367 - 0.620)	0.540*** (0.407 - 0.718)
55-64	0.365*** (0.305 - 0.437)	0.345*** (0.264 - 0.450)	0.372*** (0.290 - 0.477)	0.355*** (0.292 - 0.431)	0.646 (0.368 - 1.134)	0.477** (0.244 - 0.933)	0.219*** (0.109 - 0.439)	0.148*** (0.071 - 0.312)	0.431*** (0.315 - 0.590)	0.352*** (0.264 - 0.468)	0.465*** (0.332 - 0.650)
High School	1.079 (0.856 - 1.360)	1.195 (0.927 - 1.541)	0.575** (0.362 - 0.914)	0.586*** (0.430 - 0.800)	1.710* (0.937 - 3.121)	1.182 (0.735 - 1.901)	1.46 (0.656 - 3.250)				
Some College	1.05 (0.833 - 1.323)	1.138 (0.889 - 1.456)	0.579** (0.366 - 0.916)	0.558*** (0.410 - 0.761)	1.718* (0.958 - 3.082)	1.454 (0.928 - 2.278)	1.045 (0.499 - 2.191)				
College Grad	0.724*** (0.569 - 0.922)	0.924 (0.703 - 1.214)	0.392*** (0.249 - 0.618)	0.371*** (0.271 - 0.508)	1.286 (0.705 - 2.349)	1.318 (0.777 - 2.234)	0.747 (0.350 - 1.594)				
Low Income	1.280*** (1.147 - 1.428)			1.485*** (1.318 - 1.673)	1.264* (0.964 - 1.657)	0.89 (0.638 - 1.242)	1.093 (0.758 - 1.574)	0.692 (0.402 - 1.191)	1.365*** (1.137 - 1.638)	1.254*** (1.059 - 1.485)	1.503*** (1.248 - 1.811)
Black	0.677*** (0.591 - 0.776)	0.525*** (0.425 - 0.648)	0.800** (0.674 - 0.951)					0.231*** (0.125 - 0.426)	0.635*** (0.481 - 0.839)	0.676*** (0.545 - 0.838)	0.838 (0.674 - 1.042)
Hispanic	0.619*** (0.514 - 0.745)	0.412*** (0.331 - 0.514)	0.948 (0.735 - 1.222)					0.261*** (0.148 - 0.459)	0.485*** (0.355 - 0.664)	0.682** (0.499 - 0.933)	1.146 (0.851 - 1.544)
Other	0.907 (0.751 - 1.096)	0.734* (0.535 - 1.007)	1.015 (0.803 - 1.283)					0.511* (0.247 - 1.057)	1.125 (0.693 - 1.827)	0.812 (0.605 - 1.091)	0.973 (0.734 - 1.291)
Married	0.573***	0.559***	0.604***	0.565***	0.661***	0.658***	0.533***	0.9	0.575***	0.541***	0.558***

	(0.521 - 0.630)	(0.478 - 0.652)	(0.536 - 0.681)	(0.509 - 0.628)	(0.495 - 0.882)	(0.485 - 0.892)	(0.367 - 0.775)	(0.576 - 1.406)	(0.476 - 0.694)	(0.462 - 0.633)	(0.479 - 0.650)
Children	0.996	1.043	0.985	1.008	1.158	0.996	0.841	1.271	1.084	0.909	1.012
	(0.900 - 1.102)	(0.888 - 1.225)	(0.865 - 1.122)	(0.901 - 1.128)	(0.890 - 1.506)	(0.728 - 1.363)	(0.528 - 1.340)	(0.805 - 2.007)	(0.875 - 1.344)	(0.758 - 1.090)	(0.859 - 1.191)
Health Coverage	0.765***	0.790**	0.676***	0.606***	0.732	0.972	0.955	0.798	0.727**	0.728***	0.754*
	(0.661 - 0.885)	(0.660 - 0.946)	(0.538 - 0.850)	(0.513 - 0.716)	(0.500 - 1.074)	(0.683 - 1.382)	(0.550 - 1.660)	(0.516 - 1.232)	(0.570 - 0.927)	(0.575 - 0.922)	(0.557 - 1.020)
Constant	0.513***	0.638***	1.001	1.187	0.135***	0.211***	0.581	1.586	0.534***	0.581***	0.288***
	(0.371 - 0.707)	(0.456 - 0.892)	(0.574 - 1.746)	(0.795 - 1.772)	(0.058 - 0.316)	(0.106 - 0.418)	(0.220 - 1.532)	(0.676 - 3.720)	(0.370 - 0.769)	(0.410 - 0.824)	(0.190 - 0.436)
Observations	408,006	397,988	407,335	406,672	290,643	320,724	328,673	289,480	395,146	400,636	404,766

Note: Referent group = No State Preemption of Labor Laws; Control variables include age, income, education, race, relationship status, children, health insurance coverage.
*** $p<0.01$, ** $p<0.05$.

Table A.11. Fully Controlled Weighted Multivariate Logistic Regression Models for Number of State Preemption Laws on Self-rated Mental Health for Men, and by subgroups; Presented as Odds Ratios.

	Full Sample	Low Income	High Income	White	Black	Hispanic	Other	<High School	High School	Some College	College
1 Preemption	1.012	1.086	0.955	0.929	0.862	1.256	0.679	0.817	1.07	1.032	0.867
	(0.867 - 1.181)	(0.831 - 1.419)	(0.791 - 1.154)	(0.791 - 1.091)	(0.493 - 1.507)	(0.849 - 1.857)	(0.423 - 1.089)	(0.482 - 1.385)	(0.812 - 1.411)	(0.785 - 1.356)	(0.675 - 1.114)
2+ Preemption	1.053	0.934	1.086	1.024	1.108	0.759	1.061	1.024	1.023	1.011	1.056
	(0.944 - 1.174)	(0.774 - 1.127)	(0.949 - 1.242)	(0.905 - 1.158)	(0.758 - 1.620)	(0.532 - 1.082)	(0.703 - 1.602)	(0.690 - 1.521)	(0.848 - 1.234)	(0.835 - 1.226)	(0.866 - 1.288)
25-34	1.009	0.933	1.113	1.111	0.984	0.981	0.689	0.951	0.972	1.067	1.244
	(0.870 - 1.170)	(0.746 - 1.166)	(0.905 - 1.370)	(0.941 - 1.312)	(0.562 - 1.724)	(0.651 - 1.479)	(0.399 - 1.189)	(0.549 - 1.648)	(0.769 - 1.228)	(0.824 - 1.380)	(0.908 - 1.704)
35-44	0.876	0.746**	1	0.973	0.814	0.822	0.878	0.932	0.813	0.895	1.184
	(0.734 - 1.047)	(0.568 - 0.981)	(0.790 - 1.266)	(0.801 - 1.183)	(0.428 - 1.551)	(0.480 - 1.408)	(0.486 - 1.586)	(0.539 - 1.610)	(0.604 - 1.094)	(0.654 - 1.225)	(0.819 - 1.711)
45-54	0.593***	0.593***	0.657***	0.674***	0.566*	0.561*	0.491**	0.483**	0.525***	0.665***	0.898
	(0.494 - 0.711)	(0.429 - 0.820)	(0.522 - 0.829)	(0.555 - 0.817)	(0.308 - 1.042)	(0.290 - 1.086)	(0.241 - 0.998)	(0.265 - 0.882)	(0.379 - 0.729)	(0.496 - 0.893)	(0.621 - 1.297)
55-64	0.452***	0.424***	0.519***	0.466***	0.559	0.642	0.308***	0.448***	0.314***	0.591***	0.683**
	(0.372 - 0.549)	(0.313 - 0.576)	(0.400 - 0.673)	(0.377 - 0.576)	(0.264 - 1.181)	(0.358 - 1.149)	(0.152 - 0.627)	(0.248 - 0.808)	(0.233 - 0.423)	(0.411 - 0.849)	(0.473 - 0.987)
High School	1.053	1.285*	0.707**	0.688***	0.629	1.931***	0.636				
	(0.837 - 1.325)	(0.957 - 1.725)	(0.513 - 0.975)	(0.524 - 0.903)	(0.295 - 1.343)	(1.242 - 3.004)	(0.305 - 1.325)				
Some College	1.062	1.572***	0.652***	0.625***	0.668	2.668***	0.757				
	(0.835 - 1.350)	(1.157 - 2.137)	(0.472 - 0.901)	(0.473 - 0.824)	(0.310 - 1.443)	(1.722 - 4.133)	(0.366 - 1.569)				
College Grad	0.643***	0.992	0.420***	0.383***	0.448*	1.813**	0.569				
	(0.501 - 0.825)	(0.685 - 1.437)	(0.304 - 0.581)	(0.288 - 0.509)	(0.200 - 1.005)	(1.065 - 3.088)	(0.273 - 1.188)				
Low Income	1.278***			1.595***	1.029	0.951	1.087	0.728	1.244**	1.617***	1.589***
	(1.121 - 1.457)			(1.395 - 1.825)	(0.683 - 1.551)	(0.656 - 1.380)	(0.743 - 1.589)	(0.489 - 1.083)	(1.015 - 1.524)	(1.323 - 1.975)	(1.214 - 2.079)
Black	0.874	0.649***	1.01					0.876	0.754	0.904	1.036
	(0.724 - 1.055)	(0.491 - 0.859)	(0.793 - 1.287)					(0.419 - 1.832)	(0.533 - 1.068)	(0.670 - 1.219)	(0.754 - 1.423)
Hispanic	0.604***	0.401***	0.856					0.214***	0.554***	0.929	1.091
	(0.491 - 0.743)	(0.299 - 0.538)	(0.664 - 1.105)					(0.140 - 0.327)	(0.403 - 0.762)	(0.675 - 1.280)	(0.736 - 1.616)
Other	0.859	0.605***	0.986					0.754	0.678**	0.913	1.012
	(0.706 - 1.045)	(0.437 - 0.836)	(0.774 - 1.255)					(0.376 - 1.511)	(0.491 - 0.935)	(0.643 - 1.296)	(0.714 - 1.435)

Married	0.617*** (0.541 - 0.703)	0.740*** (0.598 - 0.916)	0.577*** (0.490 - 0.680)	0.633*** (0.553 - 0.724)	0.754 (0.491 - 1.159)	0.622** (0.405 - 0.953)	0.362*** (0.237 - 0.552)	0.680* (0.448 - 1.031)	0.708*** (0.565 - 0.887)	0.628*** (0.496 - 0.794)	0.472*** (0.374 - 0.595)
Children	0.896* (0.794 - 1.012)	0.848 (0.690 - 1.041)	0.943 (0.810 - 1.099)	0.837*** (0.732 - 0.956)	1.259 (0.873 - 1.815)	0.861 (0.590 - 1.255)	1.356 (0.904 - 2.034)	0.754 (0.529 - 1.075)	0.809** (0.657 - 0.996)	0.992 (0.802 - 1.228)	1.078 (0.830 - 1.401)
Health Coverage	0.829** (0.712 - 0.965)	0.844* (0.693 - 1.028)	0.753** (0.605 - 0.937)	0.738*** (0.618 - 0.881)	0.83 (0.532 - 1.293)	0.892 (0.619 - 1.286)	0.894 (0.566 - 1.412)	0.686* (0.451 - 1.044)	0.759** (0.605 - 0.952)	0.844 (0.656 - 1.086)	0.999 (0.722 - 1.383)
Constant	0.225*** (0.163 - 0.311)	0.285*** (0.189 - 0.430)	0.316*** (0.209 - 0.480)	0.357*** (0.252 - 0.506)	0.270*** (0.105 - 0.694)	0.084*** (0.041 - 0.171)	0.322** (0.115 - 0.900)	0.609 (0.328 - 1.133)	0.287*** (0.206 - 0.400)	0.184*** (0.128 - 0.264)	0.090*** (0.056 - 0.143)
Observations	408,006	397,988	407,335	406,672	290,643	320,724	328,673	289,480	395,146	400,636	404,766

Note: Referent group = No State Preemption of Labor Laws; Control variables include age, income, education, race, relationship status, children, health insurance coverage.
*** p<0.01, ** p<0.05.

Table A.12. Fully Controlled Weighted Multivariate Logistic Regression Models for Dimensions of State Preemption Laws on Self-rated Mental Health for Men, and by subgroups; Presented as Odds Ratios.

	Full Sample	Low Income	High Income	White	Black	Hispanic	Other	<High School	High School	Some College	College
Temporal	1.005	0.967	1	0.957	0.882	1.075	0.915	0.917	1.001	0.987	0.953
	(0.891 - 1.133)	(0.785 - 1.192)	(0.864 - 1.158)	(0.842 - 1.087)	(0.585 - 1.328)	(0.768 - 1.505)	(0.607 - 1.379)	(0.618 - 1.363)	(0.807 - 1.240)	(0.798 - 1.221)	(0.776 - 1.170)
Economic + Temporal	1.118*	1.045	1.118	1.063	1.336	0.846	0.909	1.002	1.128	1.105	1.054
	(0.984 - 1.269)	(0.847 - 1.290)	(0.955 - 1.309)	(0.923 - 1.224)	(0.856 - 2.084)	(0.544 - 1.316)	(0.590 - 1.400)	(0.610 - 1.643)	(0.910 - 1.399)	(0.880 - 1.387)	(0.853 - 1.303)
25-34	1.009	0.935	1.116	1.111	0.997	0.974	0.694	0.956	0.971	1.067	1.245
	(0.870 - 1.171)	(0.748 - 1.168)	(0.907 - 1.373)	(0.941 - 1.312)	(0.569 - 1.745)	(0.645 - 1.468)	(0.403 - 1.195)	(0.553 - 1.653)	(0.769 - 1.227)	(0.825 - 1.381)	(0.909 - 1.706)
35-44	0.877	0.746**	1.004	0.974	0.809	0.803	0.885	0.935	0.811	0.896	1.186
	(0.734 - 1.047)	(0.567 - 0.981)	(0.793 - 1.270)	(0.801 - 1.183)	(0.426 - 1.536)	(0.467 - 1.378)	(0.490 - 1.598)	(0.539 - 1.620)	(0.602 - 1.092)	(0.655 - 1.225)	(0.821 - 1.715)
45-54	0.593***	0.595***	0.659***	0.674***	0.559*	0.547*	0.492*	0.486**	0.524***	0.667***	0.899
	(0.494 - 0.711)	(0.430 - 0.823)	(0.523 - 0.831)	(0.555 - 0.817)	(0.303 - 1.032)	(0.282 - 1.060)	(0.241 - 1.004)	(0.265 - 0.891)	(0.378 - 0.728)	(0.497 - 0.896)	(0.622 - 1.298)
55-64	0.452***	0.427***	0.520***	0.465***	0.548	0.615	0.309***	0.448***	0.313***	0.593***	0.684**
	(0.372 - 0.550)	(0.315 - 0.579)	(0.401 - 0.675)	(0.376 - 0.576)	(0.258 - 1.165)	(0.339 - 1.117)	(0.151 - 0.630)	(0.248 - 0.812)	(0.232 - 0.421)	(0.413 - 0.851)	(0.473 - 0.988)
High School	1.053	1.283*	0.709**	0.688***	0.611	1.926***	0.635				
	(0.837 - 1.325)	(0.955 - 1.723)	(0.514 - 0.978)	(0.524 - 0.903)	(0.286 - 1.302)	(1.240 - 2.992)	(0.307 - 1.315)				
Some College	1.064	1.574***	0.655**	0.626***	0.652	2.658***	0.751				
	(0.837 - 1.353)	(1.158 - 2.140)	(0.474 - 0.905)	(0.474 - 0.826)	(0.303 - 1.400)	(1.719 - 4.109)	(0.364 - 1.552)				
College Grad	0.644***	0.994	0.421***	0.383***	0.437**	1.775**	0.559				
	(0.502 - 0.827)	(0.687 - 1.438)	(0.305 - 0.582)	(0.288 - 0.510)	(0.195 - 0.978)	(1.042 - 3.025)	(0.270 - 1.157)				
Low Income	1.279***			1.599***	1.048	0.93	1.084	0.735	1.240**	1.615***	1.604***
	(1.122 - 1.458)			(1.399 - 1.829)	(0.700 - 1.570)	(0.640 - 1.351)	(0.741 - 1.585)	(0.494 - 1.093)	(1.013 - 1.518)	(1.322 - 1.975)	(1.222 - 2.105)
Black	0.874	0.652***	1.01					0.881	0.755	0.902	1.032
	(0.724 - 1.056)	(0.493 - 0.863)	(0.793 - 1.286)					(0.419 - 1.855)	(0.533 - 1.068)	(0.669 - 1.216)	(0.751 - 1.418)
Hispanic	0.608***	0.414***	0.851					0.210***	0.567***	0.948	1.08
	(0.493 - 0.750)	(0.308 - 0.557)	(0.657 - 1.103)					(0.138 - 0.320)	(0.409 - 0.785)	(0.682 - 1.318)	(0.730 - 1.599)
Other	0.861	0.611***	0.987					0.753	0.682**	0.918	1.009
	(0.708 - 1.048)	(0.442 - 0.846)	(0.775 - 1.257)					(0.375 - 1.513)	(0.494 - 0.941)	(0.647 - 1.303)	(0.712 - 1.428)
Married	0.617***	0.739***	0.577***	0.634***	0.764	0.627**	0.361***	0.680*	0.709***	0.627***	0.473***

	(0.541 - 0.703)	(0.597 - 0.914)	(0.490 - 0.679)	(0.554 - 0.725)	(0.495 - 1.179)	(0.408 - 0.965)	(0.236 - 0.551)	(0.450 - 1.029)	(0.565 - 0.889)	(0.495 - 0.792)	(0.375 - 0.597)
Children	0.895*	0.846	0.943	0.835***	1.255	0.866	1.361	0.745	0.806**	0.99	1.079
	(0.793 - 1.011)	(0.689 - 1.039)	(0.810 - 1.099)	(0.731 - 0.955)	(0.872 - 1.807)	(0.592 - 1.265)	(0.906 - 2.045)	(0.521 - 1.065)	(0.655 - 0.991)	(0.800 - 1.225)	(0.831 - 1.401)
Health Coverage	0.828**	0.843*	0.752**	0.736***	0.826	0.887	0.887	0.690*	0.758**	0.845	0.994
	(0.711 - 0.963)	(0.692 - 1.027)	(0.604 - 0.936)	(0.617 - 0.879)	(0.531 - 1.284)	(0.616 - 1.277)	(0.560 - 1.404)	(0.453 - 1.051)	(0.604 - 0.951)	(0.657 - 1.087)	(0.719 - 1.374)
Constant	0.225***	0.282***	0.315***	0.357***	0.276***	0.087***	0.327**	0.611	0.287***	0.183***	0.090***
	(0.163 - 0.310)	(0.186 - 0.425)	(0.208 - 0.478)	(0.252 - 0.507)	(0.108 - 0.704)	(0.043 - 0.176)	(0.117 - 0.913)	(0.328 - 1.139)	(0.206 - 0.400)	(0.128 - 0.263)	(0.056 - 0.144)
Observations	406,614	379,746	405,656	405,562	289,084	304,676	328,404	315,710	391,227	394,014	399,510

Note: Referent group = No State Preemption of Labor Laws; Control variables include age, income, education, race, relationship status, children, health insurance coverage.
*** p<0.01, ** p<0.05.

Table A.13. Compiled state-level labor preemption laws using data from the Economic Policy Institute, 2019.

STATES	FIPS Code	MINIMUM WAGE	FAIR SCHEDULING	PREVAILING WAGE	PAID LEAVE	STATE PREEMPTION SCORE
Alabama	1	1	1		1	3
Alaska	2					0
Arizona	4			1		1
Arkansas	5	1	1		1	3
California	6					0
Colorado	8	1				1
Connecticut	9					0
Delaware	10					0
District of Columbia	11					0
Florida	12	1		1	1	3
Georgia	13	1	1	1	1	4
Hawaii	15					0
Idaho	16	1		1		2
Illinois	17					0
Indiana	18	1	1	1	1	4
Iowa	19	1	1		1	3
Kansas	20	1	1	1	1	4
Kentucky	21	1		1	1	3
Louisiana	22	1		1	1	3
Maine	23				1	1

Maryland	24				1	1
Massachusetts	25					0
Michigan	26	1	1	1	1	4
Minnesota	27					0
Mississippi	28	1			1	2
Missouri	29	1				1
Montana	30				1	1
Nebraska	31					0
Nevada	32					0
New Hampshire	33					0
New Jersey	34				1	1
New Mexico	35					0
New York	36					0
North Carolina	37	1			1	2
North Dakota	38	1				1
Ohio	39	1	1		1	3
Oklahoma	40	1			1	2
Oregon	41	1			1	2
Pennsylvania	42	1				1
Rhode Island	44	1			1	2
South Carolina	45	1			1	2
South Dakota	46					0
Tennessee	47	1	1	1	1	4

Texas	48	1				1
Utah	49	1		1		2
Vermont	50					0
Virginia	51					0
Washington	53					0
West Virginia	54					0
Wisconsin	55	1			1	2
Wyoming	56					0
TOTALS		*26*	*9*	*11*	*23*	

Note: 19 states & DC have enacted 0 labor preemption laws. 31 states have enacted 1 or more labor preemption laws.

CHAPTER 2

STATE LABOR PREEMPTION AND HEALTH CARE ACCESS FOR WORKERS WITH A HIGH SCHOOL EDUCATION OR LESS

Abstract

US state preemption laws are on the rise and scholars suggest these laws may have serious consequences for health (Pomeranz & Pertschuk, 2017). However, the history of US state preemption policymaking points to its potential to advance or hamper health. Thus, more critical evaluations that are grounded in advancing a health equity agenda (Carr et al., 2020) are needed to assess the potential health effects of these policies. Therefore, this study utilized a health equity lens to examine whether state preemption of four labor laws including minimum wage, prevailing wage, paid leave, and fair scheduling ordinances were associated with cost-related barriers to health care for US workers with a high school education or less. I also assessed whether health care outcomes differed by economic or temporal dimensions of state labor preemption and explored potential variation in health care outcomes by worker's gender, race/ethnicity, and health coverage. Using 2019 data from the Behavioral Risk Factor Surveillance System (BRFSS) Survey (Centers for Disease Control and Prevention, 2019) merged with state-level preemption law measures (Economic Policy Institute, 2019), I employed a series of weighted bivariate and multivariate logistic regression models to examine whether the number of state preemption laws, or the type of state preemption laws enacted were associated with cost-related barriers to health care for US workers with a high school education or less. Models were stratified by worker's gender, race/ethnicity, and health coverage. Findings suggest female workers with a high school education or less that lived in states with multiple preempted labor laws were at significantly higher odds of reporting cost-related barriers to health care

regardless of health coverage, and this association was pronounced for Black and white female workers. Female workers with no health coverage that lived in states with both economic and temporal labor preemption laws were at increased odds of experiencing cost-related barriers to health care suggesting that both protected time and health coverage may be important factors for worker's health. Notably, Black male workers were at significantly higher odds of experiencing barriers to health care in states with multiple preemption laws. Findings support evidence that racial inequities in health may be exacerbated by state preemption. This study contributes to calls for more research exploring preemptions potential to mitigate or exacerbate health inequities and supports growing evidence that increases in state preemption may have significant consequences for population health (Carr et al., 2020; Crosbie & Schmidt, 2020; Montez, 2020; Pomeranz & Pertschuk, 2017; Wolf et al., 2021).

Introduction

United States (US) preemption laws are on the rise and may have serious consequences for health (Pomeranz & Pertschuk, 2017). Preemption allows state governments to restrict the authority of local governments when the two authorities come into conflict about a particular issue. Research supports these concerns and finds different state preemption laws are associated with declines in life expectancy (Montez, 2018), increases in infant mortality rates (Wolf, Monnat & Montez, 2021), delayed medical care, and poor self-rated health (Melton-Fant, 2020).

However, preemption is not inherently harmful and has the potential to advance or hamper health. Historically, states enacted preemption laws to harmonize standards at state and local levels (Briffault, 2018). Yet, in recent years, preemption has been used to deliberately stifle local policymaking despite the needs and desires of local communities (Montez et al., 2020; Riverstone-Newell, 2017). This has impeded local governments from enacting legislation across several issues including minimum wage increases, smoke-free bans, and paid leave policies (Riverstone-Newell, 2017).

This tension was exemplified most recently with the patchwork public health measures enforced during the COVID-19 pandemic. Some states passed stay-at-home orders with a regulatory floor that allowed local municipalities to enforce protective public health measures based on local conditions (Davidson & Haddow, 2020). Other states, however, preempted localities from enforcing restrictions or mitigation efforts that were stricter than state mandates despite local needs or infection rates (Davidson & Haddow, 2020). Scholars argue that this type of COVID-related preemption resulted in a lack of uniform public health responses that worsened health inequities and disproportionately impacted people of color, women, and low-income workers (Haddow et al., 2021).

Moreover, state preemption has the potential to improve upon or eliminate labor protections that act as important buffers for the health of low wage workers. For instance, state preemption of local minimum wage increases could exacerbate financial insecurity and lead low-wage and low-income workers to delay needed health care despite being at greater risk for more chronic illnesses and having higher overall medical utilization and costs than their higher income counterparts (Cooper, 2019; Levin-Scherz & Nyce, 2019).

The heterogeneous effects of preemption on population health highlights the necessity for more critical evaluations that are grounded in advancing a health equity agenda (Carr et al., 2020). Therefore, this study utilizes a health equity lens to examine the association between state preemption of four labor laws and cost-related barriers to health care access for workers with a high school education or less across the United States (US). I consider whether outcomes vary by factors shown to impact health care access including gender, race/ethnicity, and health insurance (Lenhart, 2020; Chen et al., 2016).

Conceptual Framework

This study draws on the constrained choices model (Bird & Reiker, 2008) and fundamental cause theory (FCT) (Link & Phelan, 1995) which mutually emphasize the importance of contextual and individual factors for health. The constrained choices model asserts that policy contexts can have unintended and cumulative effects on individuals' choices, behaviors, and decisions for creating a healthy lifestyle (Bird & Rieker, 2008) such as utilizing health care. Importantly, constrained choice theory suggests these constraints differently affect men and women's agency and opportunities for health which can have heterogeneous consequences (Bird & Rieker, 2008). For instance, when applied to labor policies and health, the constrained choices model implies workplace policies that regulate employees' work schedules and time may produce more constraints and subsequently fewer choices for female workers with children than for males subjected to the same workplace standards given evidence that women are disproportionately affected by daily time commitments, often spending more of their time on household and family responsibilities than men (BLS, 2019). Moreover, these policies tend to disproportionately affect low skilled workers, or those with a high school education or less (Leigh & Du, 2018).

Similarly, fundamental cause theory asserts that individuals' ability to access resources and engage in health enhancing behaviors are the result of fundamental social conditions in which people live and work (Phelan et al., 2010; Link & Phelan, 1995). Inequality in working conditions and resources prevent some groups of workers, particularly those in low wage jobs, from deploying the resources necessary to avoid disease, seek treatment, and adopt healthy behaviors. In other words, upstream conditions such as the governing bodies and policy environments responsible for wielding preemption, determines the downstream factors that impact an individual's life chances. Applied here, FCT suggests that workers employed in jobs that provide autonomy and adequate pay are privy to a broad range of resources (i.e., time, money) that advantage their health (Mirowsky & Ross, 2007). In contrast, workers employed in jobs where their resources are constrained (i.e., time and pay) are at a disadvantage for health.

Considered together, the constrained choices model and fundamental cause theory suggest that worker's health is simultaneously and differentially shaped by the resources, choices, and opportunities made available, which are shaped by the social conditions and policy contexts in which individuals live. Applying these frameworks to preemption laws and health suggests that state governments which restrict local authorities from passing labor laws that attempt to evenly distribute resources and regulate working conditions may disadvantage the health opportunities for workers disproportionately affected by these laws which most often include women, low wage workers, and workers of color (Huizar & Lathrop, 2019). Thus, this study examines whether variations in state preemption laws and health care access are patterned by gender, race/ethnicity, as well as insurance coverage.

State Labor Preemption and Health Care Access

This study focused on the association between labor preemption and cost-related barriers to health care given existing evidence that differences in state labor laws have varying effects on health care access and utilization, particularly by gender and race (Waidmann & Rajan, 2000). For instance, studies show higher state minimum wages are associated with decreases in unmet medical need (McCarrier et al., 2011), increases in the ability to afford needed health care and the frequency of routine checkups (Lenhart, 2020), and improvements in access to care for Black and Latina women (Narain & Zimmerman, 2019). State paid sick leave laws are associated with increases in health care utilization (Lamsal et al., 2021; Peipins et al., 2021; DeRigne et al., 2017) and state paid family leave policies are linked to increases in postpartum care utilization (Steenland et al., 2021).

I also examined whether different dimensions of preemption have varying effects on health care access given theoretical and empirical evidence suggesting economic and temporal pathways may differentially shape worker's health (Schneider & Harknett, 2019; Carre & Tilly, 2018; Kalleberg, 2011). For instance, minimum wage laws have an economic impact on worker's earnings, income, material benefits, and status (Leigh, Leigh & Du, 2019) which are important and well-documented mechanisms through which labor laws affect workers' health and well-being (Leigh, Leigh & Du, 2019) and which may be critical for bolstering access to health care and other social determinants of health (Adler & Newman, 2002; Nelson et al., 2004).

Time is another important social determinant of health often regulated by the broader labor policy context (Strazdins et al., 2015). Although time is equally distributed to all, the demands on and autonomy to control one's time varies across workers that can lead to time constraints or protections for health and health behaviors (Venn & Strazdins, 2017). This is exemplified in fair scheduling laws which standardize employee work schedules and directly dictate workers ability to devote more or less time to health-promoting activities.

Studies show irregular and unpredictable work hours and schedules are associated poor health (Schneider & Harknett, 2019; Cho, 2017), anxiety, depression (Bara & Arber, 2009), poor self-rated health and mental health (Cho, 2017), psychological distress, poor sleep quality, and unhappiness (Schneider & Harknett, 2019) as well as child behavioral problems (Ros Pilarz, 2021) and reduced enrollment in early care and education programs (Ros Pilarz et al., 2019). In fact, recent research suggests time may be a stronger predictor of worker well-being than economic factors (Schneider & Harknett, 2019; Golden, 2015) and is worthy of more evaluation. Therefore, this study examines whether economic and temporal differences in state preemption laws differently shape cost-related health care access, which will have important implications for worker's health as well as targeted policymaking.

Aims

The aims of this paper addressed the following questions: (1) Are increases in the number of state preempted labor laws including minimum wage, prevailing wage, fair scheduling, and paid leave associated with cost-related barriers to accessing health care for US workers with a high school education or less? (2) Do economic or temporal dimensions of state labor preemption laws differentially shape health care access for workers with a high school education or less? (3) Are health outcomes patterned by worker's gender, race/ethnicity, or health coverage status?

Methods

Data

This study uses 2019 health data from the from the Behavioral Risk Factor Surveillance System (BRFSS) Survey, a nationally representative survey that collects annual state data on U.S. residents' health-related risk behaviors, chronic health conditions, and use of preventive services in all 50 states as well as the District of Columbia (Centers for Disease Control and Prevention, 2019). Data from 49 states are included in this study as BRFSS excluded New Jersey in its 2019 data collection. The BRFSS survey is administered by landline telephone or cellular telephone to randomly selected, non-institutionalized adults. In 2019, BRFSS collected data on 418,268 individuals with a median overall response rate of 49.4% (Centers for Disease Control and Prevention, 2020).

Data on state labor preemption laws was aggregated by the Economic Policy Institute (2019), which analyzed state labor preemption laws in all 50 states from 1984 to 2019. The four labor laws used in this study are (1) state minimum wage preemption laws that prohibit cities and counties from establishing minimum wages above the state or federal minimum wage (n=26 states), (2) State paid leave preemption laws which prohibit localities from requiring employers to provide employees paid sick days or paid family leave (n=23 states), (3) State fair scheduling preemption laws which restrict local governments from governing work schedules (n=9 states); and (4) state prevailing wage preemption laws which prohibit localities from requiring municipal contractors to pay workers a prevailing wage of at least the local median wage for a given type of work (n=11 states) (Economic Policy Institute, 2019).

Analytic Sample

To capture workers most likely impacted by the policies considered in this study (i.e. those in low skilled or low wage jobs), the analytic sample was restricted to employed individuals of working age (18-64) with a high school education or less, similar to methods employed in other studies (Horn et al., 2017; Leigh et al., 2019; Wehby et al., 2020; Kuroki, 2021) (n=40,829). After excluding individuals with missing information on variables used in the analysis as described below which included gender (n=6,308), race (n=5,749), smoking (n=4,258), obesity (n=2,396), self-rated health (n=5,473), marital status (n=6,085), health coverage (n=6,032), the final analytic sample consisted of 34,521 individuals. Note, the number of dropped respondents for each of the variables described here are unduplicated. Respondents may be missing on one or more variables.

Measures

Cost-Related Barriers to Health Care

The primary outcome variable was cost-related barriers to health care. Respondents were asked, “Was there a time in the past 12 months when you needed to see a doctor but could not because of cost?” Responses were categorized as yes or no, similar to previous studies that examined the association between state policies and cost-related barriers to health care (McCarrier et al., 2011; Levin-Scherz & Nyce, 2019).

Number of State Preempted Labor Laws

The number of preempted labor laws for each state was based on state restriction of any local minimum wage, paid leave, fair scheduling, or prevailing wage laws as of 2019. For each state, I summed the total number of preemptive actions and assigned a score 0, 1, or 2+ laws.

Dimensions of State Preempted Labor Laws

The type of preemption enacted in each state was categorized as economic or temporal. Temporal-based policies refer to those regulating work schedule predictability and the length and intensity of working hours (Julia et al., 2017). In this study, fair scheduling laws are the only temporal-based preemption law within this domain. Economic-based labor policies encompass material and wage-related benefits associated with employment (Julia et al., 2017) and include minimum wage, paid leave, and prevailing wage laws. States were categorized as having no preemption of any labor laws, economic-based preemption, or economic- and temporal-based preemption.

Covariates

Covariates included sociodemographic characteristics including respondent's gender (male or female), age (18-24, 25-34, 35-44, 45-54, 55-64), marital status (married or not), and race/ethnicity (White, Black, Hispanic, Other) as well as risk factors associated with health care utilization such as smoking status (smoker or not), body mass index (obese or overweight, normal), self-reported health (good or poor), and health care coverage in 2019 (coverage or no coverage) similar to studies examining state labor policies and health care access (McCarrier et al., 2011).

Analytic Strategy

Estimates were weighted according to BRFSS' complex sampling design (Centers for Disease Control and Prevention, 2019) and analyses were conducted using STATA's *svy* suite of commands (StataCorp, 2019). Given empirical and theoretical evidence that labor policies impact the health of men and women differently (Bullinger, 2019; Horn et al., 2017; Averett et al., 2017; Bird & Reiker, 2008), analyses were conducted separately for the sample of male and female workers. First, weighted descriptive statistics were conducted to describe the analytic sample (Table 2.1). Additionally, weighted bivariate analyses were conducted to examine associations between each indicator of state labor preemption and health care access by race/ethnicity, and for men and women separately (Table 2.2). I also conducted weighted bivariate analyses to examine the association between gender and health care access by race and health coverage for men and women separately (Table 2.3). Next, I employed weighted multivariate logistic regression models while accounting for clustering of standard errors at the state level, consistent with other studies that examined state-level policies on individual-level outcomes (Loll & Hall, 2019; Melton-Fant, 2020) (Table 2.4 and 2.5). Models were adjusted for covariates using AIC, a goodness of fit estimate. To assess for variation in outcomes among subgroups, models were stratified by race/ethnicity and health coverage (i.e., creating an interaction effect) and presented separately for men and women. Results from the logistic regression models are presented as odds ratios (OR) with 95% confidence intervals (CI).

Results

Table 2.1 presents characteristics of the weighted sample. Most of the sample consisted of male workers with a high school education or less (63%) as compared to female workers with a high school education or less (37%), and for both sexes the largest percentage of workers fell between 25 and 34 years old (25.2% of the male sample and 22.3% of the female sample, respectively). The largest proportion of the analytic sample identified as white (56.3% of men and 53.3% of women) followed by Hispanic (27.7% of men and 25.3% of women), Black (10.6% of men and 15.5% of women), and other race (5.5% of men and 6% of women). Males were more likely to be married (46.9%) as compared to their female counterparts (41.3%), and a larger proportion of females (80%) had health care coverage than males (77.5%). Approximately

25.5% of males and 23.1% of females were smokers and 25.5% of males and 23.1% of females were overweight or obese, respectively. Females were more likely to experience cost-related barriers to health care (22.8%) as compared to males (15.8%). The largest proportion of male and female workers with a high school education or less that lived in states that had preempted two or more labor laws (39.9% of males and 41.2% of females, respectively). Similarly, more females lived in states that had enacted preemption of labor laws with economic and economic *and* temporal dimensions (44.7% and 19.5%, respectively) as compared to males (43.7% and 19.3%, respectively).

Table 2.2 presents the weighted bivariate analysis of each state preemption measure and cost-related barriers to medical care for men and women and by race, separately. For the full sample of men and women, the highest percentages of workers who experienced cost-related barriers to health care occurred in states with 2 or more preempted labor policies (16.6% for males and 24.6% for females, respectively), although the association was only statistically significant for women. Female and male workers that lived in states with economic preemption had the highest percentage of reported barrier to accessing medical care (24.7% for females and 16.5% for males, respectively), although this association was only significant for females. Overall, the full sample of female workers with a high school education or less had higher rates of cost-related barriers to health care regardless of the type of preemption enacted. The proportion of White, Black, and Hispanic female workers with cost-related barriers to medical care was greatest in states with 2 or more preemption laws (23.0% for White female workers, 25.3% for Black female workers, and 32.8% for Hispanic workers, respectively), although the association was only significant for White and Black female workers with less than a high school education. The greatest proportion of White male workers lived in states with 1 preemption law

(15.5%) and economic preemption laws only (15.9%) as compared to Black, Hispanic, and Other race male workers who primarily lived in states with 2 or more preemption laws (18.0%, 22.9%, and 20.9%, respectively) and economic and temporal preemption (21.2%, 24.0%, and 23.1%, respectively). Among male workers, the only statistically significant associations appeared for White male workers with less than a high school education.

Table 2.3 presents weighted bivariate analyses of the association between cost-related barriers to health care and gender by race and health coverage. Results show female workers with less than a high school education, across all racial and ethnic groups as well as health coverage status, made up a larger proportion of the low wage workforce with cost-related barriers to health care as compared to their male counterparts. In particular, Hispanic female workers comprised a statistically significant proportion of workers with less than a high school education with cost-related barriers to health care (27.9%) and more than half of the full sample of female workers with a high school education or less who experienced cost-related barriers to health care had no health coverage (51.1%).

Tables 2.4 and 2.5 show results from the weighted multivariate logistic regression models for each state preemption variable on health care access for women (table 2.4) and men (table 2.5) separately, after adjusting for gender, age, income, race, marital status, children, and health coverage, and stratified by race and health care coverage (see fully controlled tables in Appendix, Tables B.1 – B.4). In table 2.4, the total sample of female workers with a high school education or less that lived in states with 2 or more preempted labor laws were at increased odds of reporting an inability to access health care as compared with women that lived in states with no preemption or only 1 preemption law. When examining for race effects (i.e. interaction effects), findings show white female workers with a high school education or less and Black female workers with a high school education or less that lived in states with 2 or more labor preemption laws were at significantly higher odds of experiencing barriers to health care as compared to those that lived in states with no preemption (Table 2.4). The associations were not statistically significant for the sample of female Hispanic and other race groups. The odds of reporting cost-related barriers to medical care were increased and statistically significant for female workers that lived in states with 2 or more preemption as laws regardless of health care coverage as compared to those that lived in states with no preemption, suggesting health coverage does not protect against the cost-related burdens associated with accessing medical care for female workers with a high school education or less.

When examining the association between dimensions of labor preemption and health care access for females, I found female workers with a high school education or less that lived in states with any type of preemption (i.e., economic, or economic *and* temporal dimensions of preemption) were at increased and statistically significant odds of reporting cost-related barriers to health care (Table 2.4). This association appeared for the white and Black sample of female workers with a high school education or less (Table 2.4) such that white females and Black females that lived in states with economic or economic and temporal labor preemption were at increased odds of reporting an inability to access health care due to cost than white and Black female workers that lived in states with no preemption (Table 2.4). When stratified by health coverage, the odds of reporting cost related barriers to medical care significantly increased for females without health coverage in states with economic *and* temporal dimensions of preemption (Table 2.4).

Table 2.5 presents findings from the adjusted weighted multivariate logistic regression models for each state preemption variable on health care access for male workers with a high school education or less. I found no statistically significant association between the number of state preemptive action and health care access for the full sample of male workers with a high school education or less (Table 2.5). When stratified by race, I found that Black male workers were at increased odds of experiencing cost related barriers to health care when living in states with any number of preemption laws as compared to Black male workers that lived in states with no preemption (Table 2.5). There were no statistically significant associations across the samples of white, Hispanic, or other racial groups. Additionally, I found no statistically significant associations between increases in state preemption laws and health care access when stratified by health care coverage (Table 2.5).

Table 2.5 also shows outcomes when considering the association between dimensions of state labor preemption and health care access for male workers. I found no statistically significant associations between different dimensions of state preemption and health care access for the full sample of male workers as well as for male workers in the health coverage stratified models (Table 2.5). When stratified by race, however, results show Black male workers that lived in states with economic *and* temporal based labor laws were at increased odds of experiencing a cost-related barrier to medical care as compared to Black male workers that lived in states with economic preemption or no preemption (Table 2.5).

Sensitivity Analyses

In sensitivity analyses, I considered an alternative indicator of health care utilization that did not consider cost-related factors and access. I used a measure of respondent's last reported routine doctor check-up where respondents who reported visiting a doctor within the past year were categorized as having accessed health care routinely and those who reported 1 or more years since their last visit were categorized as not having accessed routine health care (see

Appendix, Tables B.5 – B.8). Although results show Black female workers with less than a high school education that lived in states with 1 preemption law were at increased risk of not accessing routine health care in more than a year as compared to their Black counterparts who lived in states with no preemption (Appendix, Table B.5)—similar to findings in the main analyses—the significant associations between state labor preemption laws and cost-related barriers to care disappeared for the full sample of female workers with a high school education or less as well as for white and Black female workers with a high school education or less. Results suggest cost may be an important driving factor shaping the relationship between labor preemption and health care utilization for female workers (Appendix, Table B.5 and B.6).

For males, results show that the full sample of male workers that lived in states with more preemption, and of both economic and temporal dimensions, were at decreased odds of not accessing routine health care as were Hispanic males that lived in states with 1 or more preemption laws (Appendix Tables B.7 and B.8). Again, findings suggest preemption appears to exacerbate cost-related barriers to health care but may not impact other factors that contribute to health care utilization. Unsurprisingly, findings show female and male workers with health coverage were at decreased odds of not accessing a routine doctor visit in the last year despite living in states with 2 or more preemption laws, suggesting health coverage may be a protective factor for accessing care regardless of cost (Appendix, Tables B.5 – B.8).

Additionally, I conducted analyses that removed the sample inclusion criteria of workers with a high school education or less to assess for potential variation in health care outcomes across education levels (see Appendix, Tables B.9 – B.12). Results were robust for females of all education levels (Appendix Tables B.9 and B.10). Notably, when stratified by education, female workers with a high school education and some college education were at significantly increased odds of not accessing health care due to cost, which may be explained in part by a lack of access to health coverage plans such as Medicaid. When examining the associations between state preemption laws and health care access for males, I found that the full sample of men were at significantly higher odds of reporting a cost-related barrier to medical care, regardless of race and education (Appendix Tables B.11 and B.12). Findings suggest preemption may have far reaching health consequences beyond working populations with a high school education or less which are often hypothesized to be most impacted by these policy contexts.

Discussion

This study examined whether different aspects of state labor preemption laws were associated with cost-related barriers to health care for male and female workers. I also assessed whether outcomes were patterned by race/ethnicity and health insurance coverage. This study offers new insights about the implications of state preemption laws in the labor policy domain for health care access among US workers with a high school education or less.

First, findings suggest female workers were more likely to experience cost-related barriers to health care in states with multiple instances and forms of labor preemption laws, and this relationship was pronounced for white and Black females in particular irrespective of health insurance coverage. A similar pattern emerged for Black male workers such that Black male workers that lived in states with any preempted labor laws were at significantly higher risk of reporting a cost-related barrier to health care, particularly Black male workers that lived in states with both economic and temporal preemption laws. Findings reflect persistent racial and gender inequities in healthcare, which are often linked to a lack of economic resources, employment status as well as restricted access to job-based health coverage for females and Black Americans (Kaiser Family Foundation, 2004).

Additionally, results show female workers who had no health coverage and who lived in states with temporal preemption (i.e. states where fair scheduling laws were restricted) appeared to be at much greater risk of experiencing cost-related barriers to medical care than those who had no health coverage and who lived in states with economic based preemption laws only. Findings highlight the importance of time, and temporal aspects of work specifically, as critical for health and well-being (Schneider & Harknett, 2019; Kelly et al. 2014; Moen et al. 2016; Olson et al. 2015).

Moreover, findings highlight the importance of health coverage as a potential buffer for cost-related barriers to medical care, particularly for female workers who are subjected to irregular work hours or precarious work schedules. While the Affordable Care Act has significantly improved health insurance coverage gaps (Abdus, Mistry & Selden, 2015), variations in state Medicaid expansion in addition to insurance rates and sources of coverage vary greatly among racial, ethnic and gender groups largely due to income and employment factors (Kaiser Family Foundation, 2004) and may exacerbate preemptions effects on health. Moreover, research suggests that disparities in health care could be reduced if BIPOC groups were insured at rates comparable to those of white groups (Lillie-Blanton & Hoffman, 2005). Moreover, as evidenced here, employment and labor laws have differential effects across racial groups and addressing such systemic inequalities may take different types of policies to improve population health.

This study supports growing concerns that increases in state preemption laws may have serious consequences for health and health care (Carr et al., 2020; Crosbie & Schmidt, 2020;

Montez, 2020; Pomeranz & Pertschuk, 2017; Wolf et al., 2021). While this study offers new insights into the implications of preemption and health care access, limitations exist. First, there was a high proportion of missingness, particularly for gender, that led to a large drop in respondents used in the analytic sample. Studies have noted that the proportion of missing gender data in BRFSS may be due in part to the optional nature of the BRFSS sexual orientation and gender identity (SOGI) module (Jesdale, 2021). Additionally, BRFSS asks participants about cost-related barriers to health care and does not assess for other factors that shape one's ability to access care. Despite conducting additional analyses using a measure of respondent's last reported routine doctor check-up as an alternative indicator of health care utilization that isn't related to cost specifically (see Appendix, Tables B.5 – B.8), the measures included in this study are unable to tease out the many pieces of healthcare access that are likely confounded with cost. As a result, this study is unable to examine whether additional barriers may be impacting participant's ability to access health care and whether these factors are associated with state preemption and labor conditions. Of note, given the nature of the survey question asked—whether respondents needed to see a doctor but could not because of cost—the results presented here may be subject to potential underestimation if participants were responding to the cost aspect of the question and not accounting for their inability to access health care due to other factors such as time. More research is needed to understand these barriers and the underlying mechanisms that link state preemption and health care. Moreover, this study did not control for other state-level policies and characteristics that could be contributing to individuals' ability to afford health care. For instance, whether a state had expanded its Medicaid program under the Affordable Care Act may complicate a respondent's ability to access care particularly as it relates to cost. Future research should consider how other state policies and programs may be confounding the relationship between preemption and health care. Finally, this study employs a cross-sectional research design and only considers health care outcomes at one time point. Future research should consider how state preemption laws shape health care access over time.

Conclusion

This study examined the relationship between state preemption of four labor laws and health care access for male and female workers with a high school education or less. Findings show female workers that lived in states with multiple preempted labor laws were at significantly higher odds of reporting cost related barriers to health care regardless of health coverage, and this association was pronounced for Black and white female workers. Female workers with no health coverage that lived in states with both economic and temporal labor preemption laws were at increased odds of experiencing cost-related barriers to health care suggesting that both protected time and health coverage may be important factors for worker's health. Notably, Black male workers were at significantly higher odds of experiencing barriers to health care in states with multiple preemption laws supporting evidence that racial inequities in health may be exacerbated by state preemption.

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Tables

Table 2.1. Weighted characteristics of the analytic sample of male and female workers with a high school education or less.

	Males (%) 63.0	Females (%) 37.0
Age		
18-24	19.3	17.5
25-34	25.2	22.3
35-44	21.1	20.7
45-54	19.7	19.9
55-64	14.7	19.6
Race		
White	56.3	53.3
Black	10.6	15.5
Hispanic	27.7	25.3
Other	5.5	6.0
Marital Status		
Married	46.9	41.3
Not married	53.1	58.7
Health Care		
Coverage	77.5	80
No Coverage	22.5	20
Poor Self Rated Health	7.2	9.4
Smoker	25.5	23.1
Overweight or Obese	72.1	69.9
Cost-Related Barriers to Health Care	15.8	22.8
Number of State Preemption Laws		
0	37	35.8
1	23.1	22.9
2+	39.9	41.2
Dimensions of Preemption Enacted		
No Preemption	37	35.8
Wage Preemption	43.7	44.7
Wage + Economic Preemption	19.3	19.5

Table 2.2. Weighted bivariate analyses of the association between each state preemption exposure and cost related barriers to health care for males and females with a high school education or less, and by race.

		0 Preemption	1 Preemption Law	2+ Preemption Laws	*p-value*	0 Preemption	Economic Preemption	Economic & Temporal Preemption	*p-value*
		%	%	%		%	%	%	
Women		19.6	24.6	24.6	0.006	19.6	24.7	24.4	0.002
	White	15.3	20.9	23.0	0.001	15.3	22.1	22.9	0.000
	Black	12.9	23.6	25.3	0.015	12.9	24.8	24.9	0.007
	Hispanic	24.7	30.8	32.8	0.142	24.7	31.6	32.1	0.119
	Other	24.9	28.7	23.3	0.852	24.9	22.8	33.7	0.582
Men		15.0	15.7	16.6	0.32	15.0	16.5	15.8	0.267
	White	11.6	15.5	14.7	0.012	11.6	15.9	13.3	0.000
	Black	10.2	18.9	18.0	0.062	10.2	16.8	21.2	0.161
	Hispanic	19.6	15.6	22.9	0.104	19.6	17.8	24.0	0.332
	Other	14.7	13.3	20.9	0.187	14.7	15.9	23.1	0.168

Note: Chi-square tests are used to assess associations between each variable.

Table 2.3. Weighted bivariate analyses of the association between cost-related barriers to health care and gender, by race and health care coverage status.

	Males	**Females**	**p-value**
	15.8	22.8	0.000
White	14	20.3	0.000
Black	16.1	22.1	0.009
Hispanic	19.2	27.9	0.000
Other	16.6	25	0.031
Coverage	10.2	15.7	0.000
No Coverage	34.9	51.1	0.000

Note: Chi-square tests are used to assess associations between each variable.

Table 2.4. Weighted Multivariate Logistic Regression Model of State Preemption Indicators on Cost Related Barriers to Health Care for Females with a High School Education or Less. Presented as odds ratios (OR) with 95% confidence intervals (CI).

	Full Sample	White	Black	Hispanic	Other	Health Coverage	No Health Coverage
	OR (CI)	**OR (CI)**	**OR (CI)**	**OR (CI)**	**OR (CI)**	**OR (CI)**	**OR (CI)**
Number of Preemption Laws							
1 Preemption Law	1.19 (0.926 - 1.527)	1.41 (0.994 - 2.010)	1.74 (0.882 - 3.440)	1.02 (0.661 - 1.586)	0.92 (0.405 - 2.074)	1.18 (0.880 - 1.572)	1.26 (0.801 - 1.976)
2+ Preemption Laws	1.35*** (1.119 - 1.628)	1.52*** (1.205 - 1.921)	1.89** (1.156 - 3.103)	1.29 (0.846 - 1.978)	0.64 (0.286 - 1.433)	1.28** (1.034 - 1.588)	1.55** (1.086 - 2.207)
Dimensions of Preemption Laws							
Economic Preemption	1.25** (1.028 - 1.523)	1.47*** (1.135 - 1.904)	1.82** (1.077 - 3.068)	1.11 (0.761 - 1.623)	0.62 (0.295 - 1.298)	1.23 (0.986 - 1.546)	1.33 (0.924 - 1.905)
Economic + Temporal Preemption	1.37*** (1.115 - 1.692)	1.52*** (1.173 - 1.976)	1.92** (1.113 - 3.298)	1.26 (0.711 - 2.229)	1.24 (0.480 - 3.199)	1.26 (0.990 - 1.601)	1.77*** (1.165 - 2.684)

Note: Referent group = No State Preemption Laws; Control variables include age, race, relationship status, smoking status, BMI, health insurance coverage.
*** p<0.01, ** p<0.05.

Table 2.5. Weighted Multivariate Logistic Regression Model of State Preemption Indicators on Cost Related Barriers to Health Care for Males with a High School Education or Less. Presented as odds ratios (OR) with 95% confidence intervals (CI).

	Full Sample	White	Black	Hispanic	Other	Health Coverage	No Health Coverage
	OR (CI)	OR (CI)	OR (CI)	OR (CI)	OR (CI)	OR (CI)	OR (CI)
Number of Preemption Laws							
1 Preemption Law	0.96 (0.781 - 1.186)	1.19 (0.919 - 1.535)	2.09** (1.020 - 4.272)	0.66** (0.445 - 0.975)	0.69 (0.318 - 1.506)	0.92 (0.710 - 1.199)	1.01 (0.718 - 1.419)
2+ Preemption Laws	1.12 (0.951 - 1.310)	1.15 (0.933 - 1.407)	1.86** (1.100 - 3.149)	1.08 (0.760 - 1.542)	1.27 (0.740 - 2.192)	1.16 (0.942 - 1.421)	1.1 (0.849 - 1.412)
Dimensions of Preemption Laws							
Economic Preemption	1.04 (0.880 - 1.223)	1.23 (0.993 - 1.520)	1.73 (0.999 - 3.011)	0.78 (0.568 - 1.062)	0.87 (0.482 - 1.570)	1.04 (0.843 - 1.279)	1.06 (0.809 - 1.380)
Economic + Temporal Preemption	1.09 (0.905 - 1.309)	1.04 (0.827 - 1.297)	2.31*** (1.265 - 4.225)	1.13 (0.678 - 1.889)	1.55 (0.837 - 2.857)	1.13 (0.898 - 1.423)	1.05 (0.763 - 1.433)

Note: Referent group = No State Preemption Laws; Control variables include age, race, relationship status, smoking status, BMI, health insurance coverage.
*** p<0.01, ** p<0.05.

Appendix B

Table B.1. Fully controlled weighted logistic regression model of Number of State Preemption Laws on Cost Related Barriers to Health Care for Females with a High School Education or Less. Presented as odds ratios (OR) with 95% confidence intervals (CI).

	Full Sample	White	Black	Hispanic	Other	Health Coverage	No Health Coverage
1 Preemption Law	1.19	1.41	1.74	1.02	0.92	1.18	1.26
	(0.926 - 1.527)	(0.994 - 2.010)	(0.882 - 3.440)	(0.661 - 1.586)	(0.405 - 2.074)	(0.880 - 1.572)	(0.801 - 1.976)
2+ Preemption Laws	1.35***	1.52***	1.89**	1.29	0.64	1.28**	1.55**
	(1.119 - 1.628)	(1.205 - 1.921)	(1.156 - 3.103)	(0.846 - 1.978)	(0.286 - 1.433)	(1.034 - 1.588)	(1.086 - 2.207)
25-34	1.04	0.89	1.04	1.44	1.12	1.01	1.09
	(0.776 - 1.386)	(0.608 - 1.315)	(0.524 - 2.061)	(0.772 - 2.681)	(0.385 - 3.256)	(0.713 - 1.439)	(0.653 - 1.808)
35-44	0.81	0.64**	1.35	1.01	0.51	0.85	0.76
	(0.599 - 1.090)	(0.424 - 0.972)	(0.664 - 2.741)	(0.542 - 1.900)	(0.192 - 1.367)	(0.590 - 1.223)	(0.450 - 1.273)
45-54	0.66***	0.45***	1.23	0.76	2.26	0.67**	0.64
	(0.486 - 0.900)	(0.302 - 0.667)	(0.571 - 2.646)	(0.407 - 1.425)	(0.656 - 7.766)	(0.459 - 0.984)	(0.374 - 1.089)
55-64	0.61***	0.44***	0.6	0.77	2.77	0.58**	0.73
	(0.435 - 0.859)	(0.299 - 0.656)	(0.273 - 1.314)	(0.379 - 1.567)	(0.666 - 11.544)	(0.379 - 0.897)	(0.422 - 1.262)
Black	0.97					0.96	0.94
	(0.766 - 1.223)					(0.735 - 1.255)	(0.580 - 1.534)
Hispanic	1.09					1.13	1.06
	(0.872 - 1.372)					(0.856 - 1.504)	(0.738 - 1.528)
Other	1.33					1.39	1.13
	(0.823 - 2.161)					(0.790 - 2.429)	(0.491 - 2.589)
Married	0.82	0.84	1.01	0.85	0.49	0.78**	0.93
	(0.675 - 1.003)	(0.656 - 1.087)	(0.594 - 1.708)	(0.592 - 1.223)	(0.208 - 1.177)	(0.612 - 0.997)	(0.663 - 1.296)
Smoker	1.38***	1.38***	1.22	1.94**	1.07	1.32**	1.54**
	(1.149 - 1.661)	(1.115 - 1.708)	(0.769 - 1.926)	(1.124 - 3.351)	(0.457 - 2.511)	(1.056 - 1.639)	(1.092 - 2.171)
Overweight or Obese	1.15	1.14	1.28	1.1	1.35	1.19	1.08
	(0.951 - 1.396)	(0.902 - 1.432)	(0.782 - 2.095)	(0.732 - 1.653)	(0.553 - 3.275)	(0.941 - 1.516)	(0.772 - 1.510)
Poor Self Rated Health	2.17***	2.41***	3.17***	1.75**	1.55	2.07***	2.56***
	(1.740 - 2.706)	(1.828 - 3.167)	(1.614 - 6.240)	(1.101 - 2.771)	(0.473 - 5.057)	(1.602 - 2.678)	(1.623 - 4.047)
Health Coverage	0.19***	0.17***	0.19***	0.21***	0.13***		
	(0.157 - 0.228)	(0.136 - 0.218)	(0.115 - 0.302)	(0.149 - 0.297)	(0.058 - 0.305)		
Constant	0.82	0.96	0.42**	0.74	1.46	0.16***	0.75

	(0.603 - 1.120)	(0.669 - 1.385)	(0.184 - 0.950)	(0.403 - 1.358)	(0.438 - 4.859)	(0.115 - 0.224)	(0.453 - 1.254)
Observations	396,218	383,980	210,002	248,511	217,451	393,771	309,662

Note: Referent group = No State Preemption Laws; Control variables include age, race, relationship status, smoking status, BMI, health insurance coverage.
*** $p<0.01$, ** $p<0.05$.

Table B.2. Fully controlled weighted logistic regression model of Dimensions of State Preemption Laws on Cost Related Barriers to Health Care for Females with a High School Education or Less. Presented as odds ratios (OR) with 95% confidence intervals (CI).

	Full Sample	White	Black	Hispanic	Other	Health Coverage	No Health Coverage
Economic Preemption	1.25**	1.47***	1.82**	1.11	0.62	1.23	1.33
	(1.028 - 1.523)	(1.135 - 1.904)	(1.077 - 3.068)	(0.761 - 1.623)	(0.295 - 1.298)	(0.986 - 1.546)	(0.924 - 1.905)
Economic + Temporal Preemption	1.37***	1.52***	1.92**	1.26	1.24	1.26	1.77***
	(1.115 - 1.692)	(1.173 - 1.976)	(1.113 - 3.298)	(0.711 - 2.229)	(0.480 - 3.199)	(0.990 - 1.601)	(1.165 - 2.684)
25-34	1.04	0.89	1.03	1.45	1.03	1.01	1.08
	(0.776 - 1.386)	(0.609 - 1.313)	(0.519 - 2.063)	(0.774 - 2.696)	(0.347 - 3.081)	(0.714 - 1.437)	(0.649 - 1.805)
35-44	0.81	0.64**	1.35	1.02	0.5	0.85	0.77
	(0.601 - 1.095)	(0.424 - 0.977)	(0.659 - 2.747)	(0.545 - 1.920)	(0.188 - 1.352)	(0.590 - 1.224)	(0.456 - 1.287)
45-54	0.66***	0.45***	1.22	0.76	2.1	0.67**	0.64
	(0.487 - 0.900)	(0.302 - 0.666)	(0.568 - 2.640)	(0.406 - 1.430)	(0.609 - 7.241)	(0.459 - 0.980)	(0.374 - 1.081)
55-64	0.61***	0.44***	0.6	0.77	2.69	0.58**	0.73
	(0.435 - 0.858)	(0.299 - 0.653)	(0.270 - 1.317)	(0.379 - 1.567)	(0.638 - 11.354)	(0.379 - 0.894)	(0.422 - 1.263)
Black	0.97					0.96	0.95
	(0.769 - 1.229)					(0.736 - 1.258)	(0.585 - 1.555)
Hispanic	1.08					1.12	1.06
	(0.867 - 1.353)					(0.853 - 1.481)	(0.735 - 1.522)
Other	1.34					1.38	1.14
	(0.825 - 2.161)					(0.788 - 2.426)	(0.512 - 2.556)
Married	0.83	0.84	1.01	0.87	0.49	0.78**	0.94
	(0.678 - 1.007)	(0.657 - 1.086)	(0.600 - 1.711)	(0.597 - 1.256)	(0.207 - 1.176)	(0.614 - 0.997)	(0.673 - 1.326)
Smoker	1.38***	1.38***	1.22	1.94**	0.99	1.32**	1.53**
	(1.149 - 1.664)	(1.115 - 1.710)	(0.768 - 1.928)	(1.120 - 3.357)	(0.417 - 2.373)	(1.057 - 1.645)	(1.084 - 2.151)
Overweight or Obese	1.15	1.14	1.28	1.09	1.4	1.19	1.07
	(0.948 - 1.393)	(0.902 - 1.432)	(0.788 - 2.079)	(0.720 - 1.639)	(0.567 - 3.455)	(0.940 - 1.516)	(0.764 - 1.505)
Poor Self Rated Health	2.17***	2.40***	3.18***	1.74**	1.67	2.07***	2.55***
	(1.738 - 2.703)	(1.826 - 3.164)	(1.625 - 6.235)	(1.097 - 2.751)	(0.509 - 5.463)	(1.600 - 2.675)	(1.618 - 4.030)
Health Coverage	0.19***	0.17***	0.19***	0.21***	0.13***		
	(0.157 - 0.228)	(0.136 - 0.218)	(0.114 - 0.302)	(0.149 - 0.300)	(0.056 - 0.302)		
Constant	0.82	0.96	0.42**	0.74	1.52	0.16***	0.75
	(0.606 - 1.123)	(0.670 - 1.387)	(0.184 - 0.955)	(0.400 - 1.357)	(0.448 - 5.187)	(0.115 - 0.224)	(0.451 - 1.257)
Observations	396,218	383,980	210,002	248,511	217,451	393,771	309,662

Note: Referent group = No State Preemption Laws; Control variables include age, race, relationship status, smoking status, BMI, health insurance coverage. *** p<0.01, ** p<0.05.

Table B.3. Fully controlled weighted logistic regression model of Number of State Preemption Laws on Cost Related Barriers to Health Care for Males with a High School Education or Less. Presented as odds ratios (OR) with 95% confidence intervals (CI).

	Full Sample	White	Black	Hispanic	Other	Health Coverage	No Health Coverage
1 Preemption Law	0.96	1.19	2.09**	0.66**	0.69	0.92	1.01
	(0.781 - 1.186)	(0.919 - 1.535)	(1.020 - 4.272)	(0.445 - 0.975)	(0.318 - 1.506)	(0.710 - 1.199)	(0.718 - 1.419)
2+ Preemption Laws	1.12	1.15	1.86**	1.08	1.27	1.16	1.1
	(0.951 - 1.310)	(0.933 - 1.407)	(1.100 - 3.149)	(0.760 - 1.542)	(0.740 - 2.192)	(0.942 - 1.421)	(0.849 - 1.412)
25-34	1.23	1.38**	0.85	1.06	1.28	1.42**	1.04
	(0.989 - 1.533)	(1.046 - 1.816)	(0.387 - 1.850)	(0.672 - 1.676)	(0.674 - 2.422)	(1.061 - 1.889)	(0.742 - 1.449)
35-44	1.13	1.37**	1.27	0.78	1.11	1.24	1
	(0.899 - 1.429)	(1.015 - 1.848)	(0.583 - 2.768)	(0.507 - 1.210)	(0.516 - 2.409)	(0.911 - 1.682)	(0.702 - 1.437)
45-54	1.11	1	1.07	1.31	0.69	1.11	1.18
	(0.869 - 1.415)	(0.734 - 1.356)	(0.497 - 2.322)	(0.812 - 2.112)	(0.313 - 1.513)	(0.812 - 1.512)	(0.780 - 1.773)
55-64	0.82	0.66***	0.92	1.12	1.2	0.94	0.69
	(0.630 - 1.064)	(0.490 - 0.900)	(0.355 - 2.369)	(0.656 - 1.904)	(0.407 - 3.553)	(0.669 - 1.307)	(0.448 - 1.050)
Black	1.08					1.28	0.8
	(0.839 - 1.389)					(0.943 - 1.736)	(0.541 - 1.169)
Hispanic	1.07					1.2	0.89
	(0.881 - 1.287)					(0.928 - 1.553)	(0.680 - 1.171)
Other	1.23					1.38	0.95
	(0.930 - 1.621)					(0.978 - 1.941)	(0.611 - 1.492)
Married	0.82**	0.74***	0.77	0.92	1.05	0.72***	0.99
	(0.701 - 0.955)	(0.604 - 0.903)	(0.444 - 1.333)	(0.694 - 1.232)	(0.615 - 1.779)	(0.593 - 0.877)	(0.768 - 1.269)
Smoker	1.67***	1.81***	1.5	1.45**	2.19***	1.75***	1.55***
	(1.430 - 1.942)	(1.502 - 2.181)	(0.904 - 2.485)	(1.019 - 2.064)	(1.356 - 3.545)	(1.441 - 2.132)	(1.213 - 1.974)
Overweight or Obese	0.87*	0.96	0.79	0.79	0.9	0.87	0.86
	(0.744 - 1.015)	(0.789 - 1.173)	(0.481 - 1.281)	(0.576 - 1.080)	(0.548 - 1.472)	(0.715 - 1.060)	(0.670 - 1.097)
Poor Self Rated Health	3.26***	3.31***	2.82***	3.21***	3.33***	2.58***	5.09***
	(2.624 - 4.040)	(2.561 - 4.289)	(1.402 - 5.661)	(2.102 - 4.889)	(1.400 - 7.928)	(1.953 - 3.408)	(3.431 - 7.543)
Health Coverage	0.23***	0.21***	0.33***	0.24***	0.27***		
	(0.199 - 0.270)	(0.173 - 0.252)	(0.208 - 0.514)	(0.176 - 0.316)	(0.163 - 0.443)		
Constant	0.40***	0.37***	0.26***	0.53***	0.37***	0.09***	0.45***
	(0.313 - 0.505)	(0.279 - 0.482)	(0.129 - 0.539)	(0.332 - 0.836)	(0.178 - 0.774)	(0.065 - 0.113)	(0.318 - 0.647)
Observations	395,793	387,477	231,628	257,551	259,833	393,668	326,279

Note: Referent group = No State Preemption Laws; Control variables include age, race, relationship status, smoking status, BMI, health insurance coverage.
*** p<0.01, ** p<0.05.

Table B.4. Fully controlled weighted logistic regression model of Dimensions of State Preemption Laws on Cost Related Barriers to Health Care for Males with a High School Education or Less. Presented as odds ratios (OR) with 95% confidence intervals (CI).

	Full Sample	White	Black	Hispanic	Other	Health Coverage	No Health Coverage
Economic Preemption	1.04	1.23	1.73	0.78	0.87	1.04	1.06
	(0.880 - 1.223)	(0.993 - 1.520)	(0.999 - 3.011)	(0.568 - 1.062)	(0.482 - 1.570)	(0.843 - 1.279)	(0.809 - 1.380)
Economic + Temporal Preemption	1.09	1.04	2.31***	1.13	1.55	1.13	1.05
	(0.905 - 1.309)	(0.827 - 1.297)	(1.265 - 4.225)	(0.678 - 1.889)	(0.837 - 2.857)	(0.898 - 1.423)	(0.763 - 1.433)
25-34	1.23	1.38**	0.85	1.08	1.25	1.41**	1.04
	(0.987 - 1.529)	(1.048 - 1.819)	(0.384 - 1.878)	(0.682 - 1.696)	(0.653 - 2.391)	(1.054 - 1.878)	(0.742 - 1.449)
35-44	1.13	1.38**	1.26	0.8	1.06	1.24	1
	(0.897 - 1.426)	(1.020 - 1.859)	(0.570 - 2.765)	(0.514 - 1.236)	(0.486 - 2.297)	(0.910 - 1.681)	(0.703 - 1.436)
45-54	1.1	1	1.06	1.31	0.65	1.1	1.17
	(0.864 - 1.409)	(0.739 - 1.363)	(0.486 - 2.306)	(0.812 - 2.110)	(0.293 - 1.433)	(0.805 - 1.501)	(0.778 - 1.772)
55-64	0.82	0.67***	0.89	1.12	1.22	0.93	0.69
	(0.629 - 1.062)	(0.492 - 0.902)	(0.349 - 2.270)	(0.663 - 1.902)	(0.413 - 3.592)	(0.667 - 1.304)	(0.449 - 1.048)
Black	1.09					1.29	0.8
	(0.844 - 1.395)					(0.949 - 1.741)	(0.543 - 1.178)
Hispanic	1.05					1.17	0.88
	(0.867 - 1.264)					(0.909 - 1.516)	(0.669 - 1.155)
Other	1.22					1.37*	0.95
	(0.925 - 1.615)					(0.971 - 1.932)	(0.607 - 1.488)
Married	0.82**	0.74***	0.78	0.91	1.03	0.72***	0.98
	(0.699 - 0.954)	(0.603 - 0.902)	(0.454 - 1.340)	(0.681 - 1.227)	(0.606 - 1.746)	(0.594 - 0.879)	(0.763 - 1.266)
Smoker	1.67***	1.81***	1.49	1.45**	2.20***	1.76***	1.55***
	(1.432 - 1.945)	(1.507 - 2.183)	(0.894 - 2.490)	(1.021 - 2.051)	(1.340 - 3.622)	(1.446 - 2.142)	(1.213 - 1.974)
Overweight or Obese	0.87	0.96	0.78	0.77	0.93	0.87	0.86
	(0.745 - 1.017)	(0.789 - 1.175)	(0.476 - 1.263)	(0.565 - 1.057)	(0.570 - 1.525)	(0.718 - 1.065)	(0.670 - 1.097)
Poor Self Rated Health	3.25***	3.30***	2.83***	3.18***	3.09**	2.58***	5.07***
	(2.618 - 4.031)	(2.551 - 4.267)	(1.387 - 5.761)	(2.075 - 4.860)	(1.299 - 7.336)	(1.947 - 3.405)	(3.427 - 7.503)
Health Coverage	0.23***	0.21***	0.33***	0.24***	0.26***		
	(0.199 - 0.270)	(0.173 - 0.253)	(0.207 - 0.522)	(0.175 - 0.318)	(0.159 - 0.438)		
Constant	0.40***	0.36***	0.27***	0.53***	0.38**	0.09***	0.46***
	(0.316 - 0.510)	(0.278 - 0.480)	(0.131 - 0.547)	(0.337 - 0.845)	(0.180 - 0.799)	(0.066 - 0.114)	(0.322 - 0.656)
Observations	395,793	387,477	231,628	257,551	259,833	393,668	326,279

Note: Referent group = No State Preemption Laws; Control variables include age, race, relationship status, smoking status, BMI, health insurance coverage.
*** p<0.01, ** p<0.05.

Table B.5. Weighted Multivariate Logistic Regression Model of the Number of State Preemption Laws on Lack of Routine Doctor Check Up for Females with a High School Education or Less. Presented as odds ratios (OR) with 95% confidence intervals (CI).

	Full Sample	White	Black	Hispanic	Other	Health Coverage	No Health Coverage
1 Preemption Law	0.97	0.92	2.26**	0.73	1.65	0.91	1.14
	(0.767 - 1.221)	(0.686 - 1.238)	(1.051 - 4.854)	(0.479 - 1.117)	(0.637 - 4.291)	(0.698 - 1.195)	(0.730 - 1.784)
2+ Preemption Laws	0.84	0.92	0.87	0.70	1.14	0.79**	1.05
	(0.708 - 1.000)	(0.745 - 1.145)	(0.484 - 1.577)	(0.472 - 1.053)	(0.551 - 2.377)	(0.649 - 0.958)	(0.724 - 1.513)
25-34	0.8	0.96	0.42	0.88	0.47	0.85	0.7
	(0.613 - 1.050)	(0.687 - 1.340)	(0.169 - 1.058)	(0.519 - 1.502)	(0.169 - 1.283)	(0.616 - 1.160)	(0.418 - 1.182)
35-44	0.63***	0.61***	0.7	0.59	0.56	0.64***	0.59
	(0.478 - 0.831)	(0.424 - 0.869)	(0.282 - 1.721)	(0.348 - 1.007)	(0.202 - 1.534)	(0.457 - 0.886)	(0.352 - 1.006)
45-54	0.53***	0.53***	0.55	0.52**	0.34**	0.51***	0.54**
	(0.397 - 0.701)	(0.374 - 0.755)	(0.207 - 1.455)	(0.294 - 0.922)	(0.115 - 0.988)	(0.367 - 0.722)	(0.311 - 0.947)
55-64	0.43***	0.40***	0.28**	0.51**	0.74	0.41***	0.51**
	(0.325 - 0.573)	(0.288 - 0.559)	(0.102 - 0.755)	(0.272 - 0.967)	(0.188 - 2.941)	(0.293 - 0.572)	(0.290 - 0.911)
Black	0.54***					0.55***	0.50***
	(0.411 - 0.716)					(0.393 - 0.767)	(0.301 - 0.832)
Hispanic	0.83					0.89	0.79
	(0.674 - 1.024)					(0.695 - 1.138)	(0.547 - 1.155)
Other	1.02					1.07	0.86
	(0.684 - 1.527)					(0.678 - 1.683)	(0.420 - 1.742)
Married	0.91	1	1.06	0.79	0.8	1	0.73
	(0.764 - 1.088)	(0.803 - 1.239)	(0.569 - 1.981)	(0.561 - 1.124)	(0.386 - 1.665)	(0.817 - 1.226)	(0.520 - 1.030)
Smoker	1.50***	1.42***	2.33***	1.31	1.81	1.38***	1.92***
	(1.272 - 1.778)	(1.172 - 1.713)	(1.438 - 3.781)	(0.793 - 2.169)	(0.900 - 3.624)	(1.139 - 1.666)	(1.331 - 2.760)
Overweight or Obese	0.9	0.80**	1.22	1.09	1.01	0.92	0.88
	(0.763 - 1.068)	(0.656 - 0.976)	(0.644 - 2.320)	(0.746 - 1.586)	(0.482 - 2.116)	(0.755 - 1.112)	(0.626 - 1.236)
Poor Self Rated Health	0.68***	0.65***	1.04	0.74	0.29**	0.66***	0.72
	(0.526 - 0.874)	(0.476 - 0.876)	(0.514 - 2.101)	(0.428 - 1.284)	(0.115 - 0.748)	(0.489 - 0.892)	(0.448 - 1.153)
Health Coverage	0.25***	0.22***	0.26***	0.29***	0.31***		
	(0.209 - 0.303)	(0.172 - 0.272)	(0.146 - 0.454)	(0.207 - 0.400)	(0.147 - 0.654)		
Constant	2.12***	2.42***	0.71	1.65	1.71	0.53***	2.02**
	(1.579 - 2.838)	(1.719 - 3.397)	(0.285 - 1.783)	(0.949 - 2.857)	(0.453 - 6.489)	(0.398 - 0.707)	(1.166 - 3.514)
Observations	395,832	383,250	209,990	247,384	215,312	393,506	308,189

Note: Referent group = No State Preemption Laws; Control variables include age, race, relationship status, smoking status, BMI, health insurance coverage; *** p<0.01, ** p<0.05.

Table B.6. Weighted Multivariate Logistic Regression Model of the Dimensions of State Preemption Laws on Lack of Routine Doctor Check Up for Females with a High School Education or Less. Presented as odds ratios (OR) with 95% confidence intervals (CI).

	Full Sample	White	Black	Hispanic	Other	Health Coverage	No Health Coverage
Economic Preemption	0.91	0.92	1.44	0.73	1.26	0.85	1.11
	(0.757 – 1.087)	(0.729 – 1.154)	(0.776 – 2.679)	(0.510 – 1.042)	(0.594 – 2.675)	(0.690 – 1.042)	(0.774 – 1.594)
Economic + Temporal Preemption	0.85	0.93	0.79	0.67	1.49	0.80**	1.01
	(0.693 – 1.032)	(0.734 – 1.189)	(0.408 – 1.549)	(0.361 – 1.242)	(0.635 – 3.517)	(0.640 – 0.998)	(0.633 – 1.615)
25-34	0.8	0.96	0.45	0.88	0.44	0.85	0.7
	(0.612 – 1.050)	(0.687 – 1.340)	(0.179 – 1.124)	(0.520 – 1.502)	(0.162 – 1.220)	(0.616 – 1.161)	(0.419 – 1.180)
35-44	0.63***	0.61***	0.73	0.59	0.55	0.64***	0.59**
	(0.475 – 0.829)	(0.423 – 0.870)	(0.287 – 1.840)	(0.347 – 1.004)	(0.199 – 1.514)	(0.456 – 0.887)	(0.351 – 0.995)
45-54	0.53***	0.53***	0.58	0.52**	0.32**	0.52***	0.54**
	(0.397 – 0.702)	(0.374 – 0.755)	(0.209 – 1.581)	(0.293 – 0.920)	(0.112 – 0.944)	(0.368 – 0.725)	(0.312 – 0.944)
55-64	0.43***	0.40***	0.30**	0.51**	0.73	0.41***	0.51**
	(0.325 – 0.574)	(0.289 – 0.559)	(0.109 – 0.816)	(0.272 – 0.966)	(0.186 – 2.857)	(0.294 – 0.573)	(0.290 – 0.910)
Black	0.54***					0.55***	0.50***
	(0.410 – 0.713)					(0.392 – 0.765)	(0.300 – 0.828)
Hispanic	0.84					0.9	0.8
	(0.684 – 1.038)					(0.705 – 1.149)	(0.549 – 1.165)
Other	1.02					1.07	0.85
	(0.684 – 1.529)					(0.678 – 1.686)	(0.417 – 1.743)
Married	0.91	1	0.98	0.79	0.8	1	0.73*
	(0.761 – 1.084)	(0.803 – 1.239)	(0.519 – 1.847)	(0.557 – 1.128)	(0.385 – 1.645)	(0.815 – 1.224)	(0.513 – 1.027)
Smoker	1.50***	1.42***	2.28***	1.31	1.73	1.37***	1.92***
	(1.269 – 1.775)	(1.171 – 1.713)	(1.380 – 3.773)	(0.793 – 2.171)	(0.867 – 3.465)	(1.135 – 1.660)	(1.334 – 2.772)
Overweight or Obese	0.91	0.80**	1.25	1.09	1.02	0.92	0.88
	(0.764 – 1.072)	(0.655 – 0.976)	(0.655 – 2.386)	(0.745 – 1.591)	(0.484 – 2.133)	(0.755 – 1.113)	(0.627 – 1.245)
Poor Self Rated Health	0.68***	0.65***	1.04	0.74	0.31**	0.66***	0.72
	(0.526 – 0.877)	(0.476 – 0.876)	(0.496 – 2.181)	(0.428 – 1.286)	(0.122 – 0.775)	(0.490 – 0.894)	(0.449 – 1.157)
Health Coverage	0.25***	0.22***	0.27***	0.29***	0.31***		
	(0.210 – 0.304)	(0.171 – 0.272)	(0.153 – 0.481)	(0.207 – 0.401)	(0.146 – 0.662)		
Constant	2.11***	2.42***	0.66	1.65*	1.75	0.53***	2.02**
	(1.572 – 2.820)	(1.720 – 3.400)	(0.279 – 1.563)	(0.949 – 2.858)	(0.467 – 6.564)	(0.397 – 0.705)	(1.159 – 3.520)
Observations	395,832	383,250	209,990	247,384	215,312	393,506	308,189

Note: Referent group = No State Preemption Laws; Control variables include age, race, relationship status, smoking status, BMI, health insurance coverage; *** p<0.01, ** p<0.05.

Table B.7. Weighted Multivariate Logistic Regression Model of the Number of State Preemption Laws on Lack of Routine Doctor Check Up for Males with a High School Education or Less. Presented as odds ratios (OR) with 95% confidence intervals (CI).

	Full Sample	White	Black	Hispanic	Other	Health Coverage	No Health Coverage
1 Preemption Law	0.89	0.96	1.02	0.73**	1.17	0.84	1.04
	(0.754 - 1.049)	(0.785 - 1.163)	(0.544 - 1.894)	(0.528 - 0.996)	(0.532 - 2.565)	(0.690 - 1.010)	(0.743 - 1.455)
2+ Preemption Laws	0.87**	0.88	0.97	0.84	1.11	0.86**	0.91
	(0.774 - 0.986)	(0.761 - 1.007)	(0.614 - 1.537)	(0.620 - 1.142)	(0.727 - 1.701)	(0.753 - 0.986)	(0.698 - 1.190)
25-34	1.38***	1.56***	1.36	1.12	1.23	1.44***	1.24
	(1.171 - 1.635)	(1.279 - 1.913)	(0.761 - 2.446)	(0.772 - 1.617)	(0.713 - 2.118)	(1.194 - 1.744)	(0.878 - 1.745)
35-44	1.13	1.27**	0.94	1.04	0.72	1.11	1.17
	(0.944 - 1.345)	(1.016 - 1.579)	(0.498 - 1.770)	(0.728 - 1.486)	(0.361 - 1.447)	(0.906 - 1.367)	(0.827 - 1.657)
45-54	0.77***	0.70***	0.75	0.86	1.05	0.71***	0.97
	(0.631 - 0.928)	(0.557 - 0.876)	(0.387 - 1.446)	(0.569 - 1.294)	(0.430 - 2.583)	(0.570 - 0.895)	(0.658 - 1.445)
55-64	0.53***	0.60***	0.41**	0.48***	0.30***	0.53***	0.54***
	(0.445 - 0.642)	(0.486 - 0.746)	(0.202 - 0.817)	(0.306 - 0.762)	(0.149 - 0.614)	(0.432 - 0.654)	(0.359 - 0.800)
Black	0.56***					0.60***	0.44***
	(0.453 - 0.686)					(0.472 - 0.764)	(0.300 - 0.641)
Hispanic	0.84**					0.89	0.72**
	(0.721 - 0.976)					(0.743 - 1.062)	(0.538 - 0.961)
Other	0.93					0.93	0.95
	(0.732 - 1.189)					(0.698 - 1.230)	(0.593 - 1.517)
Married	0.76***	0.74***	0.78	0.79	0.75	0.79***	0.70***
	(0.678 - 0.861)	(0.644 - 0.857)	(0.503 - 1.214)	(0.606 - 1.016)	(0.475 - 1.191)	(0.687 - 0.898)	(0.536 - 0.901)
Smoker	1.44***	1.52***	1.15	1.41**	1.4	1.40***	1.54***
	(1.274 - 1.628)	(1.321 - 1.749)	(0.768 - 1.731)	(1.039 - 1.911)	(0.928 - 2.105)	(1.218 - 1.607)	(1.190 - 1.988)
Overweight or Obese	0.92	0.95	0.86	0.85	1.21	0.9	1
	(0.809 - 1.046)	(0.813 - 1.098)	(0.574 - 1.295)	(0.636 - 1.132)	(0.717 - 2.055)	(0.777 - 1.041)	(0.768 - 1.303)
Poor Self Rated Health	0.79**	0.96	0.98	0.54**	0.47	0.74**	0.89
	(0.634 - 0.992)	(0.759 - 1.206)	(0.349 - 2.748)	(0.333 - 0.863)	(0.201 - 1.089)	(0.561 - 0.988)	(0.613 - 1.299)
Health Coverage	0.35***	0.32***	0.42***	0.38***	0.31***		
	(0.306 - 0.404)	(0.266 - 0.388)	(0.279 - 0.618)	(0.299 - 0.485)	(0.181 - 0.514)		
Constant	1.73***	1.67***	0.93	1.70***	1.54	0.62***	1.67***

	(1.414 - 2.115)	(1.306 - 2.132)	(0.512 - 1.704)	(1.181 - 2.453)	(0.830 - 2.851)	(0.517 - 0.743)	(1.161 - 2.408)
Observations	394,644	386,693	230,202	254,347	256,912	392,937	322,972

Note: Referent group = No State Preemption Laws; Control variables include age, race, relationship status, smoking status, BMI, health insurance coverage; *** p<0.01, ** p<0.05.

Table B.8. Weighted Multivariate Logistic Regression Model of the Dimensions of State Preemption Laws on Lack of Routine Doctor Check Up for Males with a High School Education or Less. Presented as odds ratios (OR) with 95% confidence intervals (CI).

	Full Sample	White	Black	Hispanic	Other	Health Coverage	No Health Coverage
Economic Preemption	0.89	0.91	1.02	0.79	1.19	0.86**	1
	(0.787 - 1.017)	(0.784 - 1.059)	(0.632 - 1.648)	(0.606 - 1.025)	(0.698 - 2.028)	(0.742 - 0.993)	(0.766 - 1.317)
Economic + Temporal Preemption	0.85**	0.88	0.91	0.67	1	0.84**	0.86
	(0.735 - 0.972)	(0.751 - 1.036)	(0.540 - 1.537)	(0.438 - 1.024)	(0.583 - 1.722)	(0.715 - 0.976)	(0.627 - 1.172)
25-34	1.38***	1.57***	1.36	1.12	1.22	1.44***	1.24
	(1.171 - 1.635)	(1.283 - 1.919)	(0.756 - 2.454)	(0.775 - 1.622)	(0.708 - 2.107)	(1.194 - 1.743)	(0.878 - 1.747)
35-44	1.13	1.27**	0.94	1.05	0.72	1.11	1.18
	(0.945 - 1.347)	(1.019 - 1.583)	(0.499 - 1.775)	(0.736 - 1.507)	(0.360 - 1.448)	(0.906 - 1.367)	(0.835 - 1.671)
45-54	0.77***	0.70***	0.75	0.85	1.05	0.71***	0.98
	(0.631 - 0.929)	(0.558 - 0.878)	(0.389 - 1.452)	(0.566 - 1.285)	(0.422 - 2.633)	(0.569 - 0.894)	(0.662 - 1.458)
55-64	0.53***	0.60***	0.41**	0.48***	0.30***	0.53***	0.54***
	(0.445 - 0.642)	(0.487 - 0.747)	(0.204 - 0.824)	(0.304 - 0.759)	(0.149 - 0.609)	(0.432 - 0.654)	(0.361 - 0.802)
Black	0.56***					0.60***	0.43***
	(0.452 - 0.684)					(0.472 - 0.764)	(0.296 - 0.634)
Hispanic	0.84**					0.88	0.72**
	(0.719 - 0.971)					(0.737 - 1.054)	(0.542 - 0.958)
Other	0.93					0.93	0.95
	(0.730 - 1.187)					(0.697 - 1.228)	(0.595 - 1.506)
Married	0.76***	0.74***	0.77	0.78	0.75	0.79***	0.69***
	(0.677 - 0.860)	(0.644 - 0.856)	(0.499 - 1.201)	(0.600 - 1.006)	(0.473 - 1.196)	(0.687 - 0.898)	(0.535 - 0.903)
Smoker	1.44***	1.52***	1.15	1.41**	1.41	1.40***	1.54***
	(1.274 - 1.629)	(1.317 - 1.744)	(0.769 - 1.732)	(1.037 - 1.904)	(0.934 - 2.125)	(1.219 - 1.610)	(1.188 - 1.988)
Overweight or Obese	0.92	0.94	0.86	0.85	1.21	0.9	1
	(0.809 - 1.046)	(0.813 - 1.097)	(0.577 - 1.286)	(0.634 - 1.131)	(0.693 - 2.112)	(0.777 - 1.042)	(0.771 - 1.307)
Poor Self Rated Health	0.79**	0.96	0.98	0.54**	0.47	0.74**	0.89
	(0.633 - 0.992)	(0.758 - 1.207)	(0.351 - 2.755)	(0.336 - 0.870)	(0.204 - 1.058)	(0.560 - 0.988)	(0.614 - 1.302)
Health Coverage	0.35***	0.32***	0.42***	0.38***	0.31***		
	(0.306 - 0.404)	(0.266 - 0.388)	(0.280 - 0.621)	(0.299 - 0.485)	(0.183 - 0.515)		
Constant	1.73***	1.67***	0.93	1.71***	1.54	0.62***	1.66***
	(1.416 - 2.117)	(1.307 - 2.133)	(0.511 - 1.700)	(1.183 - 2.465)	(0.833 - 2.836)	(0.518 - 0.744)	(1.156 - 2.388)
Observations	394,644	386,693	230,202	254,347	256,912	392,937	322,972

Note: Referent group = No State Preemption Laws; Control variables include age, race, relationship status, smoking status, BMI, health insurance coverage; *** p<0.01, ** p<0.05.

Table B.9. Weighted Multivariate Logistic Regression Models of Number of State Preemption Laws on Cost Related Barriers to Health Care for Sample of Women of all education, and by subgroups; Presented as Odds Ratios.

	Full Sample	White	Black	Hispanic	Other	Health Coverage	No Health Coverage	< High School	High School	Some College	College
1 Preemption Law	1.30***	1.34***	1.36	1.18	1.56	1.33***	1.28	0.93	1.34**	1.54***	1.21
	(1.131 - 1.499)	(1.130 - 1.583)	(0.933 - 1.996)	(0.878 - 1.578)	(0.847 - 2.868)	(1.137 - 1.546)	(0.933 - 1.766)	(0.548 - 1.581)	(1.011 - 1.781)	(1.194 - 1.984)	(0.991 - 1.477)
2+ Preemption Laws	1.28***	1.23***	1.52***	1.51**	0.97	1.25***	1.44***	1.22	1.43***	1.31***	1.11
	(1.160 - 1.423)	(1.098 - 1.382)	(1.179 - 1.969)	(1.092 - 2.074)	(0.660 - 1.429)	(1.116 - 1.397)	(1.129 - 1.849)	(0.821 - 1.819)	(1.161 - 1.772)	(1.109 - 1.548)	(0.930 - 1.318)
25-34	0.91	0.95	0.74	1.17	0.55	0.86	1.07	1.1	1	0.9	0.9
	(0.766 - 1.073)	(0.770 - 1.161)	(0.481 - 1.134)	(0.792 - 1.717)	(0.288 - 1.056)	(0.717 - 1.035)	(0.749 - 1.518)	(0.568 - 2.121)	(0.726 - 1.383)	(0.690 - 1.186)	(0.696 - 1.177)
35-44	0.70***	0.69***	0.7	0.98	0.33***	0.67***	0.82	0.98	0.73*	0.75**	0.68**
	(0.585 - 0.840)	(0.555 - 0.868)	(0.454 - 1.081)	(0.642 - 1.497)	(0.165 - 0.643)	(0.548 - 0.821)	(0.569 - 1.192)	(0.523 - 1.827)	(0.522 - 1.028)	(0.558 - 0.995)	(0.503 - 0.923)
45-54	0.66***	0.55***	0.75	0.94	0.77	0.63***	0.76	0.72	0.62***	0.74**	0.68***
	(0.553 - 0.794)	(0.443 - 0.688)	(0.478 - 1.175)	(0.611 - 1.441)	(0.379 - 1.584)	(0.520 - 0.776)	(0.517 - 1.109)	(0.386 - 1.360)	(0.438 - 0.890)	(0.552 - 0.993)	(0.510 - 0.907)
55-64	0.56***	0.50***	0.51***	0.66	0.86	0.50***	0.93	1.17	0.44***	0.62***	0.44***
	(0.460 - 0.678)	(0.404 - 0.627)	(0.320 - 0.819)	(0.403 - 1.091)	(0.348 - 2.136)	(0.398 - 0.618)	(0.628 - 1.380)	(0.595 - 2.320)	(0.315 - 0.625)	(0.462 - 0.830)	(0.323 - 0.608)
Black	0.97					1.02	0.77	1.09	0.94	0.97	0.86
	(0.843 - 1.109)					(0.883 - 1.177)	(0.554 - 1.069)	(0.625 - 1.898)	(0.721 - 1.213)	(0.767 - 1.234)	(0.691 - 1.074)
Hispanic	1.24***					1.31***	1.08	1.2	0.98	1.08	1.58***
	(1.071 - 1.447)					(1.098 - 1.563)	(0.822 - 1.410)	(0.787 - 1.833)	(0.727 - 1.324)	(0.827 - 1.422)	(1.158 - 2.161)
Other	1.19					1.16	1.33	3.11**	0.92	1.35	1.07
	(0.956 - 1.493)					(0.903 - 1.496)	(0.808 - 2.192)	(1.244 - 7.771)	(0.579 - 1.471)	(0.926 - 1.982)	(0.773 - 1.486)
Married	0.65***	0.60***	0.76	0.74**	0.62**	0.62***	0.82	0.70	0.91	0.69***	0.50***
	(0.582 - 0.719)	(0.534 - 0.683)	(0.567 - 1.011)	(0.565 - 0.963)	(0.401 - 0.970)	(0.547 - 0.693)	(0.641 - 1.040)	(0.480 - 1.023)	(0.730 - 1.142)	(0.579 - 0.821)	(0.423 - 0.587)
Smoker	1.70***	1.79***	1.80***	1.57**	1.24	1.66***	1.78***	1.72***	1.32***	1.76***	1.59***
	(1.531 - 1.896)	(1.582 - 2.016)	(1.320 - 2.444)	(1.080 - 2.290)	(0.784 - 1.966)	(1.476 - 1.877)	(1.396 - 2.260)	(1.156 - 2.564)	(1.070 - 1.617)	(1.493 - 2.074)	(1.290 - 1.970)
Overweight or	1.25***	1.28***	1.26	1.16	1.36	1.25***	1.25	1.46	1.09	1.17	1.26***

Obese											
	(1.124 - 1.381)	(1.137 - 1.430)	(0.917 - 1.736)	(0.880 - 1.538)	(0.895 - 2.066)	(1.120 - 1.402)	(0.982 - 1.594)	(0.956 - 2.231)	(0.882 - 1.341)	(0.983 - 1.404)	(1.075 - 1.474)
Poor Self Rated Health	2.51***	2.63***	3.03***	2.17***	1.85**	2.45***	2.82***	1.58**	2.49***	2.30***	3.17***
	(2.199 - 2.858)	(2.255 - 3.056)	(2.071 - 4.445)	(1.512 - 3.124)	(1.091 - 3.140)	(2.117 - 2.825)	(2.004 - 3.972)	(1.031 - 2.413)	(1.936 - 3.196)	(1.866 - 2.841)	(2.495 - 4.034)
Health Coverage	0.18***	0.16***	0.22***	0.21***	0.13***			0.20***	0.18***	0.20***	0.16***
	(0.157 - 0.202)	(0.135 - 0.183)	(0.159 - 0.297)	(0.160 - 0.269)	(0.078 - 0.206)			(0.145 - 0.288)	(0.146 - 0.228)	(0.165 - 0.254)	(0.122 - 0.198)
Constant	0.77**	0.91	0.56**	0.70	1.63	0.15***	0.62***	0.63	0.86	0.72**	0.85
	(0.634 - 0.940)	(0.726 - 1.130)	(0.323 - 0.972)	(0.459 - 1.068)	(0.830 - 3.195)	(0.123 - 0.176)	(0.428 - 0.885)	(0.289 - 1.376)	(0.612 - 1.219)	(0.521 - 0.992)	(0.585 - 1.224)
Observations	408,568	407,321	290,549	317,514	334,043	408,336	356,871	292,707	394,668	401,049	404,670

Note: Referent group = No State Preemption Laws; Control variables include age, race, relationship status, smoking status, BMI, health insurance coverage; *** p<0.01, ** p<0.05.

Table B.10. Weighted Multivariate Logistic Regression Models of Number of Dimensions Preemption Laws on Cost Related Barriers to Health Care for Sample of Women of all education, and by subgroups; Presented as Odds Ratios.

	Full Sample	White	Black	Hispanic	Other	Health Coverage	No Health Coverage	< High School	High School	Some College	College
Economic Preemption	1.33***	1.33***	1.44***	1.30**	1.33	1.33***	1.36**	1.01	1.39***	1.48***	1.21**
	(1.190 - 1.478)	(1.173 - 1.505)	(1.092 - 1.887)	(1.001 - 1.692)	(0.833 - 2.129)	(1.179 - 1.495)	(1.053 - 1.746)	(0.673 - 1.507)	(1.108 - 1.732)	(1.229 - 1.776)	(1.026 - 1.435)
Economic + Temporal Preemption	1.20***	1.14**	1.56***	1.38	0.84	1.16**	1.43**	1.35	1.43***	1.19	0.98
	(1.073 - 1.350)	(1.001 - 1.308)	(1.155 - 2.110)	(0.938 - 2.038)	(0.530 - 1.344)	(1.019 - 1.311)	(1.067 - 1.915)	(0.829 - 2.212)	(1.138 - 1.804)	(0.978 - 1.436)	(0.810 - 1.184)
25-34	0.91	0.94	0.74	1.16	0.54*	0.86	1.07	1.08	1	0.9	0.9
	(0.765 - 1.072)	(0.769 - 1.160)	(0.479 - 1.137)	(0.787 - 1.705)	(0.280 - 1.051)	(0.717 - 1.034)	(0.747 - 1.521)	(0.563 - 2.087)	(0.727 - 1.385)	(0.691 - 1.185)	(0.693 - 1.172)
35-44	0.70***	0.69***	0.7	0.98	0.32***	0.67***	0.83	0.99	0.73	0.75**	0.68**
	(0.584 - 0.838)	(0.554 - 0.866)	(0.452 - 1.084)	(0.640 - 1.493)	(0.158 - 0.636)	(0.548 - 0.819)	(0.571 - 1.197)	(0.527 - 1.847)	(0.522 - 1.032)	(0.559 - 0.995)	(0.501 - 0.915)
45-54	0.66***	0.55***	0.75	0.93	0.76	0.63***	0.76	0.73	0.62***	0.74**	0.68***
	(0.552 - 0.792)	(0.443 - 0.687)	(0.475 - 1.171)	(0.605 - 1.424)	(0.369 - 1.571)	(0.519 - 0.773)	(0.518 - 1.110)	(0.386 - 1.364)	(0.438 - 0.889)	(0.553 - 0.990)	(0.508 - 0.905)
55-64	0.56***	0.50***	0.51***	0.66	0.84	0.50***	0.93	1.19	0.44***	0.62***	0.44***
	(0.458 - 0.676)	(0.403 - 0.626)	(0.319 - 0.820)	(0.403 - 1.085)	(0.337 - 2.110)	(0.397 - 0.617)	(0.629 - 1.382)	(0.602 - 2.347)	(0.315 - 0.623)	(0.463 - 0.829)	(0.320 - 0.603)
Black	0.97					1.02	0.77	1.09	0.94	0.97	0.86
	(0.843 - 1.109)					(0.881 - 1.176)	(0.555 - 1.075)	(0.627 - 1.898)	(0.723 - 1.216)	(0.762 - 1.227)	(0.691 - 1.075)
Hispanic	1.23***					1.30***	1.06	1.18	0.98	1.08	1.56***
	(1.064 - 1.429)					(1.095 - 1.544)	(0.806 - 1.388)	(0.772 - 1.802)	(0.727 - 1.308)	(0.828 - 1.409)	(1.156 - 2.102)
Other	1.19					1.16	1.33	3.14**	0.92	1.35	1.07
	(0.952 - 1.488)					(0.899 - 1.491)	(0.809 - 2.172)	(1.254 - 7.844)	(0.579 - 1.469)	(0.918 - 1.975)	(0.773 - 1.486)
Married	0.65***	0.60***	0.76	0.74**	0.63**	0.62***	0.82	0.71*	0.92	0.69***	0.50***
	(0.582 - 0.720)	(0.535 - 0.684)	(0.569 - 1.018)	(0.567 - 0.979)	(0.403 - 0.977)	(0.547 - 0.693)	(0.643 - 1.047)	(0.485 - 1.031)	(0.733 - 1.144)	(0.578 - 0.819)	(0.425 - 0.590)
Smoker	1.71***	1.79***	1.80***	1.58**	1.2	1.67***	1.78***	1.72***	1.32***	1.77***	1.60***
	(1.534 - 1.902)	(1.588 - 2.024)	(1.322 - 2.443)	(1.083 - 2.295)	(0.750 - 1.907)	(1.479 - 1.882)	(1.397 - 2.260)	(1.153 - 2.553)	(1.070 - 1.619)	(1.497 - 2.083)	(1.296 - 1.979)

Overweight or Obese	1.25*** (1.126 - 1.384)	1.28*** (1.141 - 1.435)	1.27 (0.921 - 1.741)	1.16 (0.875 - 1.533)	1.33 (0.870 - 2.034)	1.26*** (1.121 - 1.405)	1.25 (0.979 - 1.594)	1.46 (0.959 - 2.237)	1.09 (0.879 - 1.340)	1.17 (0.982 - 1.406)	1.26*** (1.079 - 1.480)
Poor Self Rated Health	2.51*** (2.200 - 2.860)	2.63*** (2.259 - 3.061)	3.04*** (2.078 - 4.440)	2.17*** (1.508 - 3.128)	1.86** (1.103 - 3.141)	2.45*** (2.118 - 2.827)	2.81*** (1.999 - 3.952)	1.57** (1.028 - 2.410)	2.48*** (1.933 - 3.192)	2.31*** (1.872 - 2.853)	3.18*** (2.503 - 4.034)
Health Coverage	0.18*** (0.157 - 0.202)	0.16*** (0.136 - 0.184)	0.22*** (0.158 - 0.297)	0.21*** (0.160 - 0.274)	0.13*** (0.078 - 0.211)			0.20*** (0.144 - 0.286)	0.18*** (0.146 - 0.228)	0.21*** (0.166 - 0.255)	0.16*** (0.122 - 0.198)
Constant	0.77** (0.636 - 0.941)	0.9 (0.723 - 1.124)	0.56** (0.321 - 0.975)	0.70 (0.456 - 1.068)	1.66 (0.841 - 3.262)	0.15*** (0.124 - 0.176)	0.62** (0.430 - 0.892)	0.64 (0.290 - 1.390)	0.87 (0.614 - 1.220)	0.72** (0.523 - 0.988)	0.85 (0.589 - 1.224)
Observations	408,568	407,321	290,549	317,514	334,043	408,336	356,871	292,707	394,668	401,049	404,670

Note: Referent group = No State Preemption Laws; Control variables include age, race, relationship status, smoking status, BMI, health insurance coverage; *** $p<0.01$, ** $p<0.05$.

Table B.11. Weighted Multivariate Logistic Regression Models of Number of State Preemption Laws on Cost Related Barriers to Health Care for Sample of Men of all education, and by subgroups; Presented as Odds Ratios.

	Full Sample	White	Black	Hispanic	Other	Health Coverage	No Health Coverage	< High School	High School	Some College	College
1 Preemption Law	1.14 (0.998 - 1.311)	1.23** (1.043 - 1.440)	1.62** (1.053 - 2.482)	0.91 (0.686 - 1.210)	1.09 (0.672 - 1.769)	1.15 (0.978 - 1.343)	1.14 (0.877 - 1.471)	0.70 (0.460 - 1.064)	1.14 (0.899 - 1.436)	1.27 (0.994 - 1.631)	1.30** (1.030 - 1.635)
2+ Preemption Laws	1.31*** (1.164 - 1.464)	1.25*** (1.112 - 1.415)	1.44** (1.037 - 1.990)	1.43** (1.041 - 1.976)	1.42** (1.021 - 1.983)	1.35*** (1.182 - 1.534)	1.23 (0.979 - 1.542)	0.97 (0.696 - 1.349)	1.21** (1.015 - 1.453)	1.51*** (1.211 - 1.887)	1.30*** (1.073 - 1.576)
25-34	1.31*** (1.111 - 1.545)	1.40*** (1.154 - 1.690)	1.17 (0.682 - 2.019)	1.28 (0.867 - 1.897)	1.02 (0.622 - 1.656)	1.32*** (1.076 - 1.609)	1.26 (0.964 - 1.644)	0.99 (0.613 - 1.600)	1.32** (1.035 - 1.694)	1.67*** (1.189 - 2.339)	1.22 (0.876 - 1.696)
35-44	1.14 (0.954 - 1.370)	1.18 (0.964 - 1.446)	1.33 (0.758 - 2.349)	1.09 (0.702 - 1.686)	0.89 (0.497 - 1.604)	1.05 (0.840 - 1.305)	1.35 (0.999 - 1.822)	0.92 (0.571 - 1.472)	1.25 (0.962 - 1.633)	1.27 (0.878 - 1.832)	1.27 (0.865 - 1.852)
45-54	1.02 (0.846 - 1.242)	0.91 (0.735 - 1.121)	1.08 (0.619 - 1.899)	1.38 (0.871 - 2.173)	0.78 (0.426 - 1.415)	0.91 (0.729 - 1.141)	1.35 (0.948 - 1.928)	1.15 (0.710 - 1.860)	1.02 (0.767 - 1.355)	1.06 (0.722 - 1.541)	1.02 (0.671 - 1.563)
55-64	0.89 (0.726 - 1.095)	0.72*** (0.579 - 0.897)	1.53 (0.819 - 2.869)	1.16 (0.686 - 1.972)	0.99 (0.497 - 1.964)	0.80 (0.637 - 1.010)	1.18 (0.769 - 1.819)	0.98 (0.585 - 1.646)	0.72** (0.533 - 0.985)	1.1 (0.726 - 1.653)	0.91 (0.614 - 1.352)
Black	1.12 (0.949 - 1.311)					1.22** (1.018 - 1.471)	0.88 (0.653 - 1.196)	0.86 (0.479 - 1.551)	1.11 (0.843 - 1.473)	1.05 (0.803 - 1.361)	1.16 (0.846 - 1.599)
Hispanic	1.43*** (1.228 - 1.667)					1.60*** (1.325 - 1.937)	1.08 (0.855 - 1.371)	0.87 (0.608 - 1.248)	1.03 (0.802 - 1.322)	1.88*** (1.366 - 2.591)	1.83*** (1.324 - 2.518)
Other	1.08 (0.909 - 1.292)					1.18 (0.966 - 1.446)	0.81 (0.576 - 1.135)	1.21 (0.602 - 2.440)	1.22 (0.924 - 1.612)	1.26 (0.865 - 1.830)	1.05 (0.787 - 1.391)
Married	0.67*** (0.604 - 0.749)	0.67*** (0.596 - 0.761)	0.46*** (0.324 - 0.649)	0.83 (0.638 - 1.074)	0.58*** (0.404 - 0.823)	0.65*** (0.575 - 0.736)	0.78** (0.628 - 0.963)	1.01 (0.767 - 1.336)	0.72*** (0.604 - 0.868)	0.66*** (0.536 - 0.804)	0.53*** (0.437 - 0.652)
Smoker	1.79*** (1.595 -	2.02*** (1.779 -	1.16 (0.789 -	1.53*** (1.129 -	2.13*** (1.505 -	2.00*** (1.753 -	1.42*** (1.167 -	1.38** (1.028 -	1.77*** (1.486 -	1.67*** (1.362 -	1.86*** (1.397 -

	2.001)	2.282)	1.698)	2.071)	3.025)	2.283)	1.737)	1.853)	2.116)	2.054)	2.470)
Overweight or Obese	0.94	0.97	1.02	0.76	1.41**	0.94	0.94	0.75*	0.95	0.96	1.01
	(0.834 - 1.054)	(0.857 - 1.096)	(0.716 - 1.451)	(0.563 - 1.019)	(1.018 - 1.954)	(0.819 - 1.068)	(0.753 - 1.164)	(0.557 - 1.011)	(0.795 - 1.132)	(0.750 - 1.218)	(0.822 - 1.238)
Poor Self Rated Health	3.06***	3.24***	3.64***	2.74***	2.08***	2.61***	4.56***	3.19***	3.26***	3.08***	2.06***
	(2.634 - 3.553)	(2.727 - 3.840)	(2.253 - 5.868)	(1.927 - 3.882)	(1.235 - 3.498)	(2.180 - 3.121)	(3.325 - 6.244)	(2.154 - 4.728)	(2.538 - 4.192)	(2.392 - 3.978)	(1.516 - 2.805)
Health Coverage	0.21***	0.18***	0.24***	0.24***	0.25***			0.28***	0.22***	0.20***	0.16***
	(0.187 - 0.236)	(0.161 - 0.210)	(0.170 - 0.333)	(0.189 - 0.307)	(0.175 - 0.360)			(0.210 - 0.366)	(0.185 - 0.261)	(0.161 - 0.250)	(0.121 - 0.222)
Constant	0.33***	0.35***	0.31***	0.49***	0.30***	0.07***	0.36***	0.62**	0.35***	0.30***	0.32***
	(0.277 - 0.395)	(0.288 - 0.429)	(0.184 - 0.529)	(0.336 - 0.709)	(0.177 - 0.524)	(0.058 - 0.084)	(0.269 - 0.480)	(0.388 - 0.981)	(0.260 - 0.464)	(0.213 - 0.415)	(0.208 - 0.495)
Observations	407,364	406,081	295,664	309,596	330,085	407,068	349,338	318,049	392,815	395,071	400,419

Note: Referent group = No State Preemption Laws; Control variables include age, race, relationship status, smoking status, BMI, health insurance coverage; *** p<0.01, ** p<0.05.

Table B.12. Weighted Multivariate Logistic Regression Models of Dimensions of State Preemption Laws on Cost Related Barriers to Health Care for Sample of Men of all education, and by subgroups; Presented as Odds Ratios.

	Full Sample	White	Black	Hispanic	Other	Health Coverage	No Health Coverage	< High School	High School	Some College	College
Economic Preemption	1.26*** (1.123 - 1.404)	1.29*** (1.139 - 1.464)	1.50** (1.073 - 2.091)	1.12 (0.870 - 1.438)	1.15 (0.802 - 1.656)	1.28*** (1.126 - 1.456)	1.21 (0.977 - 1.509)	0.8 (0.577 - 1.105)	1.19 (0.990 - 1.435)	1.47*** (1.197 - 1.810)	1.34*** (1.118 - 1.616)
Economic + Temporal Preemption	1.19*** (1.056 - 1.349)	1.15** (1.006 - 1.325)	1.47 (0.997 - 2.179)	1.09 (0.729 - 1.634)	1.72*** (1.168 - 2.531)	1.23*** (1.071 - 1.419)	1.09 (0.856 - 1.396)	0.99 (0.653 - 1.505)	1.17 (0.954 - 1.425)	1.26** (1.007 - 1.573)	1.18 (0.938 - 1.473)
25-34	1.31*** (1.107 - 1.541)	1.39*** (1.152 - 1.684)	1.17 (0.679 - 2.007)	1.28 (0.860 - 1.891)	1 (0.611 - 1.636)	1.31*** (1.070 - 1.602)	1.26* (0.961 - 1.641)	0.99 (0.615 - 1.605)	1.32** (1.034 - 1.691)	1.66*** (1.183 - 2.337)	1.21 (0.872 - 1.689)
35-44	1.14 (0.952 - 1.367)	1.18 (0.962 - 1.442)	1.33 (0.758 - 2.343)	1.1 (0.708 - 1.702)	0.88 (0.489 - 1.591)	1.04 (0.836 - 1.301)	1.35** (1.001 - 1.821)	0.91 (0.564 - 1.468)	1.25* (0.962 - 1.632)	1.26 (0.872 - 1.825)	1.26 (0.860 - 1.840)
45-54	1.02 (0.842 - 1.237)	0.91 (0.734 - 1.118)	1.09 (0.622 - 1.900)	1.36 (0.854 - 2.171)	0.76 (0.416 - 1.397)	0.91 (0.724 - 1.134)	1.35* (0.946 - 1.925)	1.13 (0.695 - 1.844)	1.02 (0.767 - 1.354)	1.05 (0.715 - 1.532)	1.02 (0.669 - 1.552)
55-64	0.89 (0.723 - 1.092)	0.72*** (0.578 - 0.894)	1.54 (0.825 - 2.859)	1.18 (0.684 - 2.027)	0.97 (0.489 - 1.937)	0.80* (0.632 - 1.005)	1.18 (0.767 - 1.824)	0.98 (0.582 - 1.642)	0.72** (0.533 - 0.984)	1.09 (0.717 - 1.647)	0.91 (0.610 - 1.343)
Black	1.12 (0.953 - 1.315)					1.22** (1.019 - 1.472)	0.89 (0.658 - 1.204)	0.88 (0.492 - 1.588)	1.12 (0.846 - 1.476)	1.06 (0.812 - 1.376)	1.16 (0.846 - 1.597)
Hispanic	1.39*** (1.201 - 1.615)					1.56*** (1.294 - 1.871)	1.06 (0.839 - 1.327)	0.86 (0.597 - 1.233)	1.02 (0.793 - 1.300)	1.79*** (1.322 - 2.413)	1.80*** (1.309 - 2.463)
Other	1.07 (0.902 - 1.281)					1.17 (0.957 - 1.432)	0.8 (0.572 - 1.129)	1.19 (0.584 - 2.416)	1.22 (0.922 - 1.608)	1.23 (0.850 - 1.791)	1.04 (0.784 - 1.387)
Married	0.67*** (0.603 - 0.749)	0.67*** (0.597 - 0.762)	0.46*** (0.323 - 0.647)	0.82 (0.629 - 1.065)	0.58*** (0.404 - 0.821)	0.65*** (0.575 - 0.737)	0.78** (0.625 - 0.961)	1 (0.757 - 1.326)	0.72*** (0.604 - 0.868)	0.66*** (0.538 - 0.810)	0.53*** (0.438 - 0.652)
Smoker	1.79*** (1.601 -	2.02*** (1.788 -	1.16 (0.788 -	1.52*** (1.118 -	2.12*** (1.489 -	2.01*** (1.763 -	1.43*** (1.169 -	1.38** (1.028 -	1.78*** (1.488 -	1.68*** (1.372 -	1.86*** (1.402 -

	2.008)	2.293)	1.695)	2.053)	3.004)	2.295)	1.740)	1.848)	2.118)	2.069)	2.478)
Overweight or Obese	0.94 (0.834 - 1.055)	0.97 (0.859 - 1.098)	1.02 (0.716 - 1.446)	0.74 (0.544 - 1.007)	1.43** (1.029 - 1.974)	0.94 (0.820 - 1.070)	0.94 (0.753 - 1.166)	0.75 (0.556 - 1.012)	0.95 (0.795 - 1.132)	0.96 (0.750 - 1.221)	1.01 (0.824 - 1.242)
Poor Self Rated Health	3.06*** (2.638 - 3.557)	3.23*** (2.725 - 3.834)	3.60*** (2.230 - 5.820)	2.72*** (1.910 - 3.875)	2.06*** (1.226 - 3.450)	2.61*** (2.183 - 3.128)	4.57*** (3.340 - 6.250)	3.16*** (2.139 - 4.671)	3.26*** (2.537 - 4.194)	3.11*** (2.414 - 4.016)	2.07*** (1.520 - 2.814)
Health Coverage	0.21*** (0.186 - 0.236)	0.18*** (0.161 - 0.211)	0.24*** (0.171 - 0.336)	0.24*** (0.189 - 0.310)	0.25*** (0.173 - 0.357)			0.28*** (0.211 - 0.369)	0.22*** (0.185 - 0.261)	0.20*** (0.161 - 0.251)	0.16*** (0.122 - 0.223)
Constant	0.33*** (0.280 - 0.400)	0.35*** (0.287 - 0.428)	0.31*** (0.184 - 0.528)	0.50*** (0.342 - 0.725)	0.31*** (0.180 - 0.535)	0.07*** (0.059 - 0.085)	0.36*** (0.273 - 0.488)	0.63 (0.394 - 1.006)	0.35*** (0.261 - 0.466)	0.30*** (0.216 - 0.422)	0.32*** (0.208 - 0.497)
Observations	407,364	406,081	295,664	309,596	330,085	407,068	349,338	318,049	392,815	395,071	400,419

Note: Referent group = No State Preemption Laws; Control variables include age, race, relationship status, smoking status, BMI, health insurance coverage; *** p<0.01, ** p<0.05.

CHAPTER 3

THE IMPACT OF NONSTANDARD AND IRREGULAR WORK SCHEDULES ON CARDIOVASCULAR HEALTH FOR US WORKERS AT YOUNG ADULTHOOD AND EARLY MID-LIFE

Abstract

Nonstandard and irregular work schedules have become increasingly prevalent over the last decade (Lambert et al., 2014), particularly among low wage and service sector workers in the United States (Appelbaum et al., 2003; Enchautegui, Johnson & Gelatt, 2015; Golden, 2001). A growing evidence base shows nonstandard and irregular work schedules are associated with numerous adverse health outcomes for workers subjected to these scheduling practices. Building on this literature, this study examines whether nonstandard and irregular work hours at young adulthood were associated with poor cardiovascular health (CVH) outcomes for workers at young adulthood (aged 24-32) and early mid-life (aged 33-43), and whether outcomes varied by gender, race/ethnicity, education, or employment in the service industry. This study used public and restricted biomarker data from The National Longitudinal Study of Adolescent to Adult Health (Add Health) and employed a series of weighted bivariate and multivariate logistic regression models to assess whether nonstandard or irregular work schedules were associated with CVH outcomes including obesity, diabetes, hypertension, high inflammation, and high LDL-cholesterol. Models were stratified by worker's gender, race/ethnicity, education, and occupational industry. Findings indicate workers subjected to nonstandard work scheduling practices in young adulthood were at increased risk of obesity and high inflammation at early mid-life and as a result may be at increased risk of cardiovascular disease. Of note, the health consequences of nonstandard work schedules appeared to disproportionately affect the cardiovascular health of female and Black workers as well as workers employed outside of the

service industry. Results from this study contribute to our understanding about the impacts of nonstandard and irregular work schedules on worker's health, offers important insights about CVH outcomes for workers at young adulthood and early mid-life, and informs labor policymaking agendas particularly with regard to state and local fair scheduling laws.

Introduction

The United States (US) labor market has undergone significant shifts over the last 50 years due in part to declines in labor unions and market regulation as well as a rise in globalization and a 24-hour economy (Kalleberg, 2011). These changes have led to increases in flexible employment and low-quality, precarious employment conditions (Benach et al., 2014; Howell & Kalleberg, 2019; Scott, 2004). As such, workers have experienced stagnant incomes and wages, declines in employer benefits, and unstable and unpredictable work schedules (Kalleberg, 2018). These shifts in employment are associated with widening socioeconomic disparities in health and well-being (Benach et al., 2014), and felt most severely among low-income and lower skilled workers who are disproportionately subject to poor labor conditions (Bernhardt et al., 2009) and at higher risk for chronic disease and lower life expectancy than their higher income and higher skilled counterparts (Leigh & De Vogli, 2016; Pickett & Wilkinson, 2015).

Nonstandard work hours are defined by schedules that take place outside of the standard 9 to 5 working hours (Presser, 2003). Studies show nonstandard work hours disproportionately affect lower skilled workers (Presser, 2003) and are linked to negative physical and mental health outcomes (Moreno et al., 2019; Kalil, Ziol-Guest & Levin-Epstein, 2010) as well as work-family conflicts (Maume & Sebastian, 2012) and strained parent-child relations (Han, 2008; Li et al., 2013). Irregular work schedules, on the other hand, are characterized by routine work schedule instability and uncertainty in the dates and times a worker will be required to work each week, often leaving workers with little to no input into their work hour or schedule preferences. Such scheduling practices can encompass short notice of work schedules, rotating schedules, irregular work schedules and hours, canceled shifts, and on-call shifts with little to no advanced notice and substantial last minute scheduling changes (Appelbaum et al., 2003; Clawson & Gerstel, 2015; Golden, 2001; Halpin, 2015). Consequences of these scheduling practices can limit worker's incomes and create unpredictable and stressful circumstances in workers' daily lives (Ben-Ishai, Matthews, & Levin-Epstein, 2014) and lead to health harming outcomes (e.g., Books et al., 2020; Ramin et al., 2014).

While scholars and policymakers have primarily focused on countering these inequities through economic policies which often include increases in minimum wages (Luce, 2017; Dube, Lester & Reich, 2010), emerging research suggests policy efforts should also consider temporal dimensions of work as an important lever for improving precarious work conditions that may have equal to if not more important implications for worker's well-being (Schneider & Harknett, 2019). As such, recent regulatory efforts have attempted to address schedule instability through state and local fair scheduling laws which require employers to provide workers with stable, predictable, and flexible work schedules including advanced notice of work hours or compensation for last-minute schedule changes (Economic Policy Institute, 2019).

Studies show that fair scheduling laws may have a positive impact on worker's well-being and sleep behaviors. For example, Seattle Washington's Secure Scheduling ordinance, which aimed to increase schedule predictability by requiring advanced notice of schedule changes and improve access to sufficient work hours, was shown to improve workers' subjective well-being, sleep quality, and economic security (Harknett et al., 2021). Emeryville California's Fair Workweek Ordinance, which required large retail and food service employers to provide advanced notice of schedules and to compensate workers for last-minute schedule changes, was associated with improvements in parental well-being and declines in sleep difficulty among low wage workers with families (Ananat, Glassman-Pines & Fitz-Henley, 2022).

Conceptual Framework

Theoretical frameworks suggest employment and working conditions get 'under the skin' of workers and shape health through various physiological, psychological, and behavioral pathways that influence health (Brugard & Lin, 2013; Brunner & Marmot, 2006; Link & Phelan, 1995). Time, particularly as it relates to work conditions, is an important social determinant of and resource for health and well-being (Strazdins et al., 2015). Several studies show that limited time can prevent workers from engaging in important healthy behaviors such as exercise and diet (Allen & Armstrong, 2006) and pressure on one's time can affect negative mood and impact health through bio-behavioral stress responses (Lundberg, 1993; Offer & Schneider, 2011). Moreover, autonomy and control over one's time may be essential for health and is associated with improved quality of life and subjective well-being (for a review see Mogilner, Whillans & Norton, 2018).

A growing body of literature supports this framework and demonstrates that nonstandard and irregular working hours can have a significant negative impact on many aspects of workers' quality of life and adversely affect worker's physical, mental, and behavioral health (Books et al., 2020). For instance, shift work is associated with numerous health harming outcomes including ischemic heart disease (Frost, Kolstad & Bonde, 2009), cardiovascular disease, metabolic syndrome, diabetes (Wang et al., 2011), increased odds of obesity (Han et al., Kohsro et al., 2011), shorter sleep durations (Ramin et al., 2014), increased risk of breast cancer (Wang et al., 2014), and inflammation (Bahinipati et al., 2022; Kohsro et al., 2011).

Similarly, nonstandard work schedules have been shown to interfere with circadian sleep cycles and negatively affect sleep quality (Costa 2003; Maume et al. 2009; Vogel et al. 2012; Wight, Raley, and Bianchi 2008; Schneider & Harknett, 2019) as well as exacerbate negative mental health outcomes including increased stress (Bara and Arber, 2009), anxiety, irritability (Costa 2003), poor self-rated mental health (Cho 2017; Costa 2003; Fenwick and Tausig 2001, 2004; Knutsson 2003; Presser 2003; Rajaratnam and Arendt 2001), psychological distress and unhappiness (Schneider & Harknett, 2019). Moreover, the constraints on individual's work-related time have led to behavioral problems among worker's children (Ros Pilarz, 2021) and is associated with reduced enrollment in early care and education programs (Ros Pilarz et al., 2019) as well as childhood and adolescent obesity (Miller & Han, 2008).

While evidence of the adverse health effects of nonstandard and irregular work schedules is growing, less is known about the relationship between these scheduling practices and worker's cardiovascular health (CVH) particularly for younger working adults and workers with irregular schedules during the day. Moreover, evaluating the relationship between nonstandard and irregular work schedules and CVH is important in light of concerning trends in cardiovascular disease (CVD) among younger US cohorts (Gooding et al., 2020). For instance, studies show mortality rates from CVD have increased for women aged 35-44 since 1997 (Ford & Capewell, 2002) and hospitalizations from stroke have significantly increased for men and women aged 18-44 since 1996 (George, Tong & Bowman, 2017). Despite improvements in cardiovascular care, declines in CVH have been attributed to increasing racial, ethnic and gender disparities, unhealthy lifestyle behaviors, and increases in rates of obesity, diabetes and hypertension among adults aged 18-39 (Pearson-Stuttard et al., 2016; Brown et al., 2018; Leppert et al., 2019). As such, understanding whether nonstandard or irregular work schedules are associated with poor CVH outcomes among young adult workers will have important implications for population health.

Aims

While evidence indicates nonstandard and irregular work schedules are associated with numerous aspects of worker's mental, physical, and behavioral health, less is known about the relationship between these work schedules and risk factors for cardiovascular disease among young adult workers in the US. Thus, this study investigated the association between nonstandard and irregular work schedules and several cardiovascular health outcomes for US workers at young adulthood and early mid-life. The aims of this paper addressed the following questions: (1) whether nonstandard or irregular work hours were associated with poor cardiovascular health outcomes for workers at young adulthood (aged 24-32), (2) whether nonstandard or irregular work hours in young adulthood shaped poor cardiovascular health outcomes at early mid-life (aged 33-43), and (3) whether patterns of cardiovascular health outcomes at young adulthood and early mid-life varied by gender, race/ethnicity, education or employment in the service industry.

Importantly, this study considered a unique subgroup of the workforce, adults at young adulthood (aged 23-32) and early mid-life (aged 33-44), who are likely immersed in their working years and for whom CVH will have important implications for lifetime risk of CVD (Lloyd-Jones et al., 2006). Additionally, this study examined variations in CVH outcomes by gender, race/ethnicity, education, and service industry given existing evidence that suggests service and retail industries employ the largest concentrations of hourly, wage, and low-income workers (Osterman & Shulman, 2011; Lambert, Fugiel & Henley, 2014) putting these subgroups at higher risk of experiencing health harming consequences of labor policy landscapes. Findings from this study will have important implications for understanding whether nonstandard and irregular scheduling conditions may disproportionately impact the health of workers across subgroups most likely subjected to these scheduling practices, and better inform labor policymaking agendas, particularly with regard to state and local fair scheduling laws.

Methods

Data

This study used public and restricted data from The National Longitudinal Study of Adolescent to Adult Health (Add Health) at wave 4 (2008-2009) and wave 5 (2016-2018). Add Health is a national, ongoing longitudinal study that began collecting data on a sample of US adolescents in grades 7 through 12 beginning in 1994 through adulthood (Harris, 2013). Add Health selected a nationally representative sample of students from 80 high schools and 52 feeder middle schools based on region, urbanicity, school size, school type, and ethnicity. Coordinated by the Carolina Population Center, Add Health was designed to examine the social, behavioral, and biological determinants of health across the life course. This study received Institutional Review Board approval at the University of Washington to conduct secondary data analyses under an Add Health Restricted-Use Data Contract.

Analytic Sample

At wave 4, Add Health interviewed and collected biomarker data from participants between 2007 and 2008 when participants were aged 24-32 years old (n = 15,701). At wave 5, participants were aged 33-43 years old and interviewed between 2016 and 2018 (n = 12,300), however only a subset of wave 5 respondents participated in the biomarker data collection and thus were considered for this study's sample (n = 5,380). The analytic sample used in this study consisted of those participants who were employed in wave 4 and who participated in both the wave 4 and wave 5 rounds of the in-home interview and biomarker data collections (wave 4 n =

15,291; wave 5 n = 5,030). I excluded respondents with missing data on variables described below including employment industry (wave n=411; wave 5 n=347), gender (wave 4 n=0; wave 5 n=222), education (wave 4 n=4; wave 5 n=0), race/ethnicity (wave 4 n=0; wave 5 n=205), marital status (wave 4 n=19; wave 5 n=13), and smoking status (wave 4 n=137; wave 5 n=0) as well as the wave 4 work-related variable of supervisor status (n=254) resulting in a final analytic sample of n = 14,989 at wave 4 and n = 5,010 at wave 5. Note, the number of dropped respondents for each of the variables described here are unduplicated. Respondents may be missing on one or more variables.

Measures

This study utilized various cardiovascular health indicators as defined by the American Heart Association's (AHA) Life Simple 7 metrics of ideal cardiovascular health. These indicators included BMI, cholesterol, blood pressure, glycated hemoglobin (HbA1c), healthy diet, exercise, and smoking status (Hasbani et al., 2022). Given data limitations in the Add Health survey, this study was only able to examine some of the AHA's ideal cardiovascular health measures. At wave 4, these measures included BMI, glycated hemoglobin (HbA1c), and blood pressure. At wave 5, AHA metrics assessed included BMI, glycated hemoglobin (HbA1c), blood pressure, and LDL-cholesterol. In addition, I included a measure of high sensitivity C-reactive protein (hsCRP) as an indicator of inflammation captured at both waves 4 and 5, which has shown to be useful in cardiovascular risk assessment (Greenland et al., 2010).

BMI

BMI was captured using a measurement of participants weight and height. Add Health classified BMI according to the National Institutes of Health Clinical Guidelines on the Identification, Evaluation, and Treatment of Overweight and Obesity in Adults guidelines

(Entzel et al., 2009). As such participants were categorized as underweight (16.5 - <18.5 kg/m2), normal weight (18.5 - <25 kg/m2), overweight (25 - <30 kg/m2), obese I (30 - <35 kg/m2), obese II (35 - <40 kg/m2), or obese III (≥40 kg/m2) (Entzel et al., 2009). I employed a categorical measure of BMI where respondents were grouped as underweight or normal weight, overweight, or obese (obese I, obese II, or obese III). I also used a dichotomous measure of BMI and categorized individuals as underweight/normal weight or overweight, obese I, obese II, or obese III.

Glycated hemoglobin (HbA1c)

Glycated hemoglobin (HbA1c) was measured as an indicator of diabetes. Add Health constructed a measure of diabetes using the 2011 clinical practice recommendations for the diagnosis and classification of diabetes (ADA, 2011). Respondents were classified as having levels of HbA1c that were considered normal (HbA1c ≤5.6%), pre-diabetes (HbA1c 5.7-6.4%), or diabetes (HbA1c ≥6.5%) (Whitsel et al., 2012). This study employed a categorical measure of diabetes where respondents with normal HbA1c levels were categorized with no diabetes, pre-diabetes levels of HbA1c were categorized as pre-diabetes, and diabetes levels of HbA1c were categorized as having diabetes. I also used a dichotomous measure of diabetes where individuals who were classified as normal were categorized as having no diabetes and individuals who were classified with pre-diabetes or diabetes were categorized as having diabetes risk.

Blood Pressure

Measures of systolic blood pressure (sbp) and diastolic blood pressure (dbp) were collected as indicators of hypertension and constructed by Add Health based on guidelines from the Seventh Report of the Joint National Committee on Prevention Detection, Evaluation, and Treatment of High Blood Pressure (JNC7) (Chobanian et al., 2003). As such, respondent's blood pressure was classified as normal (sbp <120 and dbp <80), pre-hypertension (sbp 120–139 or dbp 80–89), hypertension stage 1 (sbp 140–159 or dbp 90–99), or hypertension stage 2 (sbp ≥160 or dbp ≥100) (Entzel et al., 2009). This study used a categorical and dichotomous measure of hypertension where respondents who were categorized as no hypertension, pre-hypertension or hypertension (categorical measure), and dichotomized as having no hypertension if classified as normal sbp or having hypertension is sbp was classified with pre-hypertension, hypertension stage 1 or hypertension stage 2 levels (dichotomous measure).

Inflammation

High sensitivity C-reactive protein (hsCRP) was used as an indicator of inflammation and classified as low, average or high without regard to fasting status in accordance with the American Heart Association and Centers for Disease Control's clinical and public health practice recommendations regarding markers of inflammation and cardiovascular disease (Pearson et al, 2003). This study used a dichotomous measure to categorize participants' inflammation as high (hsCRP >3 mg/L) or average/low (hsCRP <1 – 3 mg/L).

Cholesterol

A measure of low-density lipoprotein cholesterol (LDL-C) was constructed based on respondent's fasting lipids at early mid-life. Add Health classified LDL-cholesterol using the National Cholesterol Education Program (NCEP) and Adult Treatment Panel (ATP) III guidelines (Whitsel et al., 2020). In this study, respondent's LDL-cholesterol was dichotomized as high if respondent's fasting LDL-C (mg/dl) was classified as borderline high (130-159 mg/dl), high (160-189 mg/dl), or very high (≥ 190 mg/dl). Respondent's LDL-cholesterol was considered optimal or low if respondent's fasting LDL-C was classified as near optimal (100-129 mg/dl) or optimal (<100 mg/dl).

Work Schedules

Participant's reported work schedules were the primary independent variable used in this study and was constructed based on the wave 4 in-home survey question that asked respondents what category best described their current job hours. Response options included: regular day, regular evening, regular night, a shift that rotates, split shifts, or irregular schedule or hours. Using a categorical measure, I classified workers as having standard, nonstandard or irregular work schedules. Standard work hours included respondents who reported their job hours as regular day; nonstandard work hours included those who stated their work hours were regular evening, regular night, a shift that rotates, or a split shift; and irregular work hours included respondents who reported their current job hours as irregular. Questions on work hours were not asked in wave 5, so the wave 4 measure was used for both the cross-sectional analysis of young adults (at wave 4) and the longitudinal analysis of early mid-life (wave 5).

Covariates

Additional sociodemographic variables associated with health used in these analyses included gender at wave 4 (male, female), measures of education at wave 4 and wave 5 (high school education or less, some college, bachelor's degree or more), a wave 4 measure of race/ethnicity (white, Black, Hispanic, other), and wave 4 and wave 5 measures of marital status (ever married or not). I also included a measure of smoking at wave 4 and wave 5 based on the number of days respondents smoked cigarettes in the last 30 days, which is an important risk factor for CVD (Roy et al., 2017). In addition, a measure of respondent's occupational industry at wave 4 was included (whether respondents were employed in the service industry or not) given evidence that service sector workers, or those in the retail and food industries, are most likely subjected to unstable and unpredictable work schedules and more likely to experience health consequences as a result (Appelbaum et al. 2003; Enchautegui, Johnson, & Gelatt, 2015; Golden, 2001). Finally, I included wave 4 measures of whether respondents were in a supervisory role, the number of hours respondents worked per week, and the length of employment at respondents' current job similar to previous studies that have examined work schedules and health (Schneider & Harknett, 2019).

Analytic Strategy

Unweighted and weighted descriptive statistics were computed to examine characteristics of the analytic sample at young adulthood (wave 4) and early mid-life (wave 5) (Table 3.1). In supplementary analyses, I conducted weighted descriptive statistics for workers in each work schedule category at young adulthood (wave 4) and early mid-life (wave 5) (see Appendix Table C.1). Next, I conducted weighted bivariate analyses to examine associations between each type of work schedule and categorical measures of obesity, diabetes, and hypertension as well as the dichotomous measures of inflammation and cholesterol at young adulthood and early mid-life (Table 3.2). To address research question 1, whether nonstandard or irregular work schedules were associated with poor cardiovascular health outcomes for workers at young adulthood, I conducted weighted multivariate logistic regression models using the dichotomous measures of CVH and adjusting for covariates using AIC, a goodness of fit measure (Table 3.3). To address research question 2, whether nonstandard or irregular work schedules at young adulthood were associated with poor cardiovascular health outcomes for workers at early mid-life, I conducted weighted multivariate logistic regression models examining work schedules (reported at wave 4) and dichotomous cardiovascular health outcomes (captured at wave 5) adjusting for covariates (Table 3.4). To address research question 3, I considered gender, racial/ethnic, educational, and occupational industry differences in the relationship between work schedules and dichotomous

CVH indicators at young adulthood and early mid-life by stratifying all models by worker's gender, race/ethnicity, education at young adulthood and early mid-life, and occupational industry (i.e. creating 3-way interactions), and adjusting for covariates (Tables 3.3 and 3.4). The other race category was excluded in the race/ethnicity stratified models due to low sample size (n=284). Finally, I conducted predicted probabilities based on the logistic regression models for the full sample of workers at young adulthood and early mid-life for each CVH indicator (see Appendix Tables C.2 and C.3). All estimates were weighted according to Add Health's complex sampling design (Chen & Harris, 2020) and analyses were conducted using STATA's *svy* suite of commands (StataCorp, 2019).

Results

Table 3.1 presents weighted and unweighted characteristics of the analytic sample at young adulthood (wave 4; aged 24-32) and early mid-life (wave 5; aged 33-43). The majority of the weighted sample reported having a standard work schedule at young adulthood (67.2%), followed by workers with a nonstandard work schedule (22.9%), and workers with irregular work schedules (10.0%). At both young adulthood and early mid-life, the weighted sample predominantly identified as white (71.2% of the sample in young adulthood and 72.8% of the sample in early mid-life) followed by Black (15.7% and 15.4% respectively), Hispanic (8.9% and 8.6% respectively) and other race (4.2% and 3.2% respectively). The largest proportion of the weighted sample had some college education at young adulthood (43.4%) as compared to the majority of the weighted sample at early mid-life who had a college degree or more (42.5%) highlighting that as the sample aged, they likely accrued more education over time. More than half of workers were married at early mid-life (57.9%) as compared to only 50.0% of workers who were married at young adulthood. Males at young adulthood comprised the largest proportion of workers (50.6%), however female workers comprised the largest share of workers at early mid-life (54.5%). Service industry workers accounted for 19.2% of the sample at young adulthood and 19.8% of the sample at early mid-life.

In terms of CVH, the most common BMI category for workers at both young adulthood and early mid-life was obesity (36.7% at wave 4 and 47.6% at wave 5) and the growth in the proportion of workers who met obesity criteria from young adulthood to early mid-life was noteworthy. In contrast, the greatest number of workers at young adulthood and early mid-life had no diabetes, and this percentage of workers with no diabetes increased over time (69.3% to 87.7%, respectively). The majority of workers at young adulthood and early mid-life met pre-hypertension criteria (48.3% at young adulthood and 42.1% at early mid-life), and the proportion of workers diagnosed with hypertension increased slightly over time from 19.4% at young adulthood to 20.4% at early mid-life. 40.6% of the sample at young adulthood had high biomarkers of C-reactive protein (inflammation) as did 36.4% of the sample at early mid-life, and 22.1% of workers presented with high LDL-cholesterol at early mid-life (Table 3.1).

Table 3.2 shows results from the weighted bivariate analyses examining the associations between work schedules and the categorical indicators of obesity, diabetes and hypertensions at young adulthood and early mid-life as well as the dichotomous indicators of inflammation and LDL-cholesterol. At young adulthood, nonstandard workers had the highest rates of obesity (39.1%) as well as the highest rates of diabetes (4.3%) as compared to workers with standard and irregular work schedules, although these associations were not statistically significant. Workers with standard work schedules had the same rates of hypertension (19.5%) and high inflammation (40.8%) as nonstandard workers, while workers with irregular schedules had the lowest rates of poor health across all four cardiovascular outcomes at young adulthood (obesity 33.9%, diabetes 3.9%, hypertension 17.7%, and high inflammation 36.9% respectively), yet none of these associations were statistically significant. At early mid-life, workers with nonstandard work schedules at young adulthood once again presented with the highest rates of obesity (53.8%), high inflammation (40.8%), and high LDL-cholesterol (24.1%), and these associations were significant for obesity and inflammation. Workers with irregular schedules at young adulthood had the highest rates of diabetes (6.1%) and hypertension (24.2%) at early mid-life, both of which were statistically significant, whereas standard workers had the lowest rates of obesity (45.5%), diabetes (4.2%), and hypertension (19.3%).

In Table 3.3, I show results from the weighted multivariate logistic regression models that examined the association between work schedules and poor CVH outcomes at young adulthood, controlling for sociodemographic and health risk factors. Models showing all control variables are available in the Appendix (see Tables C.4-C.7). Overall, findings showed no meaningful associations between nonstandard or irregular work schedules and obesity, diabetes, and high inflammation for the full sample of young adult workers and subgroups of workers by gender, race, education, and industry. Of note, Black workers with irregular work schedules were at statistically significant and increased odds of hypertension in young adulthood as compared to Black workers with standard work schedules when accounting for sociodemographic characteristics and health risk factors. There were no statistically significant patterns among work schedules and obesity for the full sample of workers and across subgroups. Some subgroups of nonstandard and irregular workers were at significantly decreased odds of diabetes, hypertension, and high inflammation. For instance, nonstandard workers with some college education were at significantly decreased odds of diabetes as compared to their counterparts with standard schedules and female workers with irregular work schedules were at decreased risk of high inflammation as compared to female workers with standard work schedules (Table 3.3).

Table 3.4 presents outcomes from the weighted multivariate logistic regression models that examined the association between work schedules at young adulthood and poor CVH outcomes at early mid-life adjusting for sociodemographic and health risk factors. Models showing all controls are available in the Appendix (see Tables C.8-C.12). Findings indicate that the full sample of nonstandard workers at young adulthood were at increased risk of obesity in early mid-life as compared to workers with standard work schedules in young adulthood, and this association was pronounced for female and Black workers with nonstandard schedules as well as nonstandard workers employed outside of the service sector. Additionally, results show that Black workers and non-service sector workers with nonstandard schedules at young adulthood were at significantly increased odds of high inflammation at early mid-life as compared to their counterparts with standard work schedules. There were no statistically significant or meaningful patterns for nonstandard or irregular workers at young adulthood and diabetes, hypertension, or high LDL-cholesterol at early mid-life.

Sensitivity Analyses

Sensitivity analyses were conducted using alternative specifications of diabetes and hypertension at young adulthood (Appendix, Table C.13) and early mid-life (Appendix, Table C.14) as well as high cholesterol at early mid-life (Appendix, Table C.14). These measures considered whether workers had a biomarker that met criteria for the given condition *or* a reported doctor's diagnosis of the given condition at each time point. Findings were similar to outcomes in the main models for diabetes and hypertension at young adulthood such that there were no meaningful or statistically significant associations among both nonstandard and irregular workers (Appendix Table C.13) which is unsurprising given the age of the sample, 24-33, and cardiovascular guidelines that do not call for assessments of hypertension among younger adult cohorts.

When examining the association between work schedules at young adulthood and the alternative measure of diabetes at early mid-life, findings suggest that irregular workers with less than a high school education were at increased odds of meeting diabetes criteria *or* receiving a doctor's diagnosis of diabetes, which was statistically significant, and nonstandard workers with a high school education or less were at statistically significant and increased odds of hypertension in early mid-life (Appendix Table C.14). Similar patterns appeared in the alternative high cholesterol models such that workers with a college degree or more who had irregular schedules in young adulthood were at increased risk of high LDL-cholesterol in early mid-life as compared to their working counterparts with standard work schedules (Appendix Table C.14), however no other meaningful patterns appeared.

Additionally, I conducted analyses using an alternative measure of obesity where respondents were categorized as overweight/obese or normal/underweight (Appendix, Tables C.15 and C.16). Findings show that for nonstandard workers the odds of overweight/obesity in young adulthood decreased for the full sample of workers, and for nearly every subgroup of nonstandard workers except for nonstandard workers with a high school education or less and nonstandard workers employed outside of the service industry, although none of these associations were statistically significant similar to outcomes in the main models for obesity (Appendix Table C.15). Of note, Hispanic workers with irregular schedules were at increased odds of overweight/obesity in young adulthood, and this association was statistically significant (Appendix Table C.15). In early mid-life, the odds of obesity for nonstandard workers once again decreased and the statistically significant associations for the full sample of nonstandard workers as well as for female, Black and non-service sector nonstandard workers disappeared when using the alternative obesity measure (Appendix Table C.16) suggesting that nonstandard work schedules have a much more significant impact on workers who meet obese BMI classifications than those who fall within overweight BMI classifications.

Finally, I conducted stricter weighted logistic regression models (i.e. change models) that examined irregular work hours at young adulthood and CVH outcomes at early mid-life adjusting for CVH outcomes at young adulthood (Appendix, Table C.13). High LDL-cholesterol was not included in this analysis as it was not captured at young adulthood (wave 4). Overall, results show that the odds of poor CVH health at early mid-life were slightly increased across subgroups. Of note, female workers with nonstandard work schedules at young adulthood were at statistically significant higher odds of hypertension at early mid-life, and Black workers with nonstandard work schedules at young adulthood were at statistically significant higher odds of high inflammation at early mid-life (Appendix, Table C.17), yet nearly all other outcomes were robust to the logistic regression models that did not control for CVH at young adulthood.

Discussion

This study examined whether nonstandard and irregular work schedules were associated with CVH outcomes for US workers at young adulthood and early mid-life. I also assessed whether CVH outcomes were patterned by worker's gender, race/ethnicity, education, and occupational industry. This study builds on prior research examining work schedules and worker health and well-being and offers new insights about the implications of work schedules on cardiovascular health for younger workers in the US over time. Moreover, this study supports a growing evidence base that finds certain types of work schedules may be associated with adverse health outcomes for workers subjected to precarious scheduling practices.

Findings from this study suggest nonstandard work schedules negatively impact some measures of cardiovascular health for US workers over time, and these consequences may disproportionally affect certain subgroups of workers more severely. For instance, female workers, Black workers, and workers employed outside of the service sector with nonstandard work schedules during young adulthood may be at greater risk of obesity as they age into early mid-life relative to their working counterparts with standard work schedules during young adulthood. Additionally, Black workers and those working outside of the service sector who held nonstandard jobs in young adulthood were at increased odds of high inflammation at early mid-life relative to their counterparts who held jobs with standard work schedules while in young adulthood. These findings support prior evidence that night shift work and job stress associated with nonstandard schedules is a risk factor for obesity (Han et al., 2011; Ramin et al., 2015; Books et al., 2017) and markers of high inflammation (Bahinipati et al., 2022; Kohsro et al., 2011).

Despite evidence to suggest irregular work schedules may have negative consequences for cardiovascular health, this study found little evidence of an association between poor CVH outcomes at young adulthood and early mid-life and irregular work schedules with exception of Black workers who were shown to be at increased odds of hypertension in young adulthood. Although these findings may be explained in part by higher incidences of chronic diseases such as hypertension, diabetes, and asthma among Black Americans (Lackland, 2014), evidence also shows that Black workers are subject to lower employment rates relative to their white counterparts and are simultaneously more likely to be employed in jobs with undesirable work hours, evening shifts, and rotating schedules (Presser, 2003). The combination of these factors has been shown to have numerous adverse physiological, psychological, and social impacts and underscores the disproportionate health consequences experienced by workers of color subject to these scheduling practices.

Additionally, I hypothesized that workers employed in service sector jobs would be at increased risk for negative CVH profiles given evidence that nonstandard and unpredictable work schedules have become increasingly prevalent in the last decade (Lambert et al., 2014), particularly among workers in the service sector who hold retail and food service jobs (Appelbaum et al., 2003; Enchautegui, Johnson & Gelatt, 2015; Golden, 2001). However, I found no evidence of any associations. In fact, workers employed in jobs with nonstandard schedules outside of the service industry were found to be at increased odds of obesity and high inflammation as they aged as compared to their counterparts with standard work schedules in non-service sector jobs, which might be explained in part by the rise of precarious jobs across all sectors of employment (Kalleberg, 2011). Such increases in precarious employment may be putting a larger swath of workers employed in various occupational industries at risk of workplace inequities and adverse health risks.

Additionally, there were notable differences between the full sample of workers at young adulthood and those workers who participated in the biomarker data collection at early mid-life that are worth considering. The sample of respondents in early mid-life had more education than the sample at young adulthood which may be explained by the ongoing acquirement of more education as the sample got older. Interestingly, the sample of workers at early mid-life experienced a significant increase in obesity and diabetes rates but a decrease in high inflammation. Also noteworthy is the dramatic decrease in pre-diabetes among the sample of workers in wave 4 and wave 5. While there are clear differences in the CVH of the samples in wave 4 and wave 5, these differences don't necessarily support any meaningful patterns about sample selection or the preexisting health status of these two groups. In fact, it's also worth considering that aspects of each sample's CVH may be masked due to a lack of or onset of symptoms and risks factors in young adulthood and early mid-life that may not likely present for these cohorts until later in life.

While access to biomarker data is a strength of this study, additional limitations exist. First, irregular work schedules were only measured at a single timepoint such that Add Health asked respondents about their employment hours and schedules at wave 4 when workers were in young adulthood and not in subsequent waves. As such, I was unable to assess the relationship between long term nonstandard or irregular work schedules for workers in early mid-life and changing CVH outcomes, and this may have attenuated the relationship between work schedules and CVH. Also, given related research, I anticipated that similar to workers with nonstandard schedules, workers with irregular work schedules would be at increased risk of poor CVH outcomes relative to their working counterparts with predictable or standard work schedules, and that these outcomes would be more pronounced as these workers aged. While one finding from this study supports this hypothesis, the evidence was limited. Finally, although this study does not make causal claims, it's important to note that the associations presented here may be bidirectional such that workers who were already in poor health may be more likely subjected to precarious working conditions such as irregular or nonstandard work schedules due to health limitations.

Importantly, because CVH and CVD is less studied in young adults than among older age groups, results suggest that this cohort is an important group that should be studied in future research. Moreover, risk factors for CVD such as obesity, high blood pressure, and smoking early in life can increase the risk of cardiovascular disease later in life, and given evidence of the increased incidence of obesity, hypertension, high blood pressure, and high LDL-cholesterol for workers at young adulthood and early mid-life included in this study, future research should continue to assess for CVH outcomes and CVD risk as workers subjected to nonstandard and irregular work schedules age.

Conclusion

This study examined the relationship between nonstandard and irregular work schedules and cardiovascular health outcomes among US workers at young adulthood and early mid-life. I also assessed for patterns in CVH by gender, race, education, and occupational industry. Findings suggest workers subject to nonstandard work scheduling practices are at greater odds of poor CVH including obesity and high inflammation, and thus may be at increased risk of cardiovascular disease later in life. Moreover, the health consequences of nonstandard work schedules appeared to disproportionately affect female and Black workers as well as workers employed outside of the service sector. Findings from this study support prior evidence that nonstandard work hours may be contributing to widening health inequities, particularly for women and BIPOC communities who are more likely to hold precarious jobs. This study offers important insights about CVH outcomes for younger workers and informs labor policymaking agendas, particularly with regard to state and local fair scheduling laws.

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Tables

Table 3.1. Characteristics of the weighted and unweighted analytic sample of workers at young adulthood (wave 4; aged 24-32) and at early mid-life (wave 5; aged 33-43).

	Young Adulthood - Wave 4 N=14,989		**Early Mid-Life - Wave 5 N=5,010**	
	Unweighted N (%)	*Weighted %*	*Unweighted N (%)*	*Weighted %*
Work Schedules				
Standard Schedules	10,130 (67.6)	67.2	3,412 (68.1)	66.2
Nonstandard Schedules	3,439 (22.9)	22.9	1,096 (21.9)	23.7
Irregular Schedules	1,420 (9.5)	10.0	502 (10.0)	10.1
Race				
White	8,780 (58.6)	71.2	3,231 (64.5)	72.8
Black	3,295 (22.0)	15.7	963 (19.2)	15.4
Hispanic	1,855 (12.4)	8.9	532 (10.6)	8.6
Other	1,059 (7.1)	4.2	284 (5.7)	3.2
Education				
High School or less	3,550 (23.7)	26.1	739 (14.8)	17.4
Some College	6,663 (43.5)	43.4	1,914 (38.2)	40.2
BA+	4,776 (33.9)	30.5	2,357 (47.1)	42.5
Married	7,465 (49.8)	50.0	2,988 (59.6)	57.9
Gender				
Female	8,012 (53.5)	49.4	3,039 (60.7)	54.5
Male	6,977 (46.5)	50.6	1,971 (39.3)	45.5
Service Industry Workers	2,802 (18.7)	19.2	889 (18.0)	19.8
Smoker	3,229 (21.5)	24.9	1,113 (22.2)	25.5
BMI				
Obese	5,439 (36.9)	36.7	2,259 (46.0)	47.5
Overweight	4,452 (30.2)	29.8	1,406 (28.6)	27.6
Normal or Underweight	4,861(33.0)	33.5	1,248 (25.4)	24.9
Glycated hemoglobin (HbA1c)				
Diabetes	605 (4.4)	3.6	199 (4.5)	4.7
Prediabetes	3,987 (29.1)	27.1	347 (7.9)	7.6
No Diabetes	9,106 (66.5)	69.3	3,843 (87.6)	87.7
Blood Pressure				
Hypertension	2,706 (18.7)	19.4	915 (19.0)	20.4
Pre-Hypertension	6,863 (47.4)	48.3	1,997 (41.5)	42.1
No Hypertension	4,916 (33.9)	32.4	1,895 (39.4)	37.5
High Inflammation (C-reactive Protein)	5,431 (40.6)	40.4	1,562 (36.4)	36.4
High LDL-Cholesterol	-	-	621 (22.6)	22.1

Table 3.2. Weighted bivariate analyses of associations between each type of work schedule and each indicator of CVH at young adulthood (wave 4) and early mid-life (wave 5). Presented as weighted proportions with 95% confidence intervals.

	Young Adulthood - Wave 4				**Early Mid-Life - Wave 5**			
	Standard Schedules N=10,130 (67.2)	***Nonstandard Schedules N=3,439 (22.9)***	***Irregular Schedules N=1,420 (10.0)***	***P-value***	***Standard Schedules N=3,412 (66.2)***	***Nonstandard Schedules N=1,096 (21.9)***	***Irregular Schedules N=502 (10.1)***	***P-value***
BMI								
Obese	36.3 (34.6-38.0)	39.1 (36.4-42.0)	33.9 (30.5-37.5)	0.107	45.5 (42.7-48.4)	53.8 (49.2-58.3)	45.7 (39.4-52.2)	0.006
Overweight	30.0 (28.7-31.3)	28.3 (26.2-30.6)	31.8 (28.7-35.0)		29.4 (27.0-31.8)	24.4 (21.1-28.1)	23.9 (19.0-29.6)	
Normal or Underweight	33.7 (31.9-35.5)	32.5 (30.1-35.1)	34.3 (30.8-38.1)		25.1 (22.6-27.8)	21.8 (18.3-25.7)	30.4 (23.8-37.9)	
Glycated hemoglobin (HbA1c)								
Diabetes	3.3 (2.7-4.2)	4.3 (3.2-5.7)	3.9 (2.7-5.6)	0.451	4.2 (3.1-5.6)	5.7 (4.0-8.3)	6.1 (3.4-10.7)	0.047
Prediabetes	27.3 (25.5-29.2)	27.0 (24.5-29.6)	26.3 (22.7-30.2)		7.1 (5.9-8.5)	10.0 (7.4-13.5)	4.9 (2.8-8.5)	
No Diabetes	69.4 (67.2-71.5)	68.7 (65.5-71.7)	69.9 (65.8-73.7)		88.8 (87.0-90.3)	84.2 (80.5-87.4)	89.0 (83.8 – 92.7)	
Blood Pressure								
Hypertension	19.5 (18.3-20.8)	19.5 (17.8-21.4)	17.7 (14.9-20.9)	0.583	19.3 (17.4-21.3)	22.1 (19.2-25.3)	24.2 (19.6-29.5)	0.015
Pre-Hypertension	48.5 (47.3-49.6)	47.0 (44.5-49.5)	49.7 (46.3-53.1)		42.3 (39.9-44.7)	44.8 (40.9-48.6)	34.3 (28.3-41.0)	
No Hypertension	32.0 (30.6-33.5)	33.5 (31.0-36.0)	32.6 (29.4-36.0)		38.5 (36.0-41.0)	33.1 (29.2-37.3)	41.4 (34.0-49.3)	
High Inflammation	40.8 (38.1-42.5)	40.8 (38.1-43.6)	36.9 (33.7-40.3)	0.129	35.2 (32.9-37.7)	40.8 (36.9-44.8)	33.9 (27.6-40.8)	0.043
High Cholesterol	-	-	-		21.8 (19.7-24.0)	24.1 (19.8-28.9)	19.9 (14.2-27.1)	0.529

Note. Chi-square tests were used to assess associations between each variable.

Table 3.3 Weighted multivariate logistic regression models examining the association between work schedules and dichotomous CVH outcomes at young adulthood (wave 4), controlling for sociodemographic and health risk factors. Presented as odds ratios with 95% confidence intervals.

	Full Sample	Female	Male	White	Black	Hispanic	Highschool or less	Some College	BA+	Service Sector	Other Industry
Obesity											
Nonstandard	1.005 (0.876 - 1.154)	0.933 (0.763 - 1.140)	1.061 (0.875 - 1.286)	0.99 (0.830 - 1.180)	1.206 (0.915 - 1.590)	0.986 (0.666 - 1.461)	1.103 (0.844 - 1.441)	0.966 (0.799 - 1.167)	0.862 (0.656 - 1.133)	0.752 (0.551 - 1.026)	1.076 (0.921 - 1.258)
Irregular	0.919 (0.758 - 1.115)	0.901 (0.651 - 1.246)	0.936 (0.722 - 1.214)	0.862 (0.700 - 1.062)	1.033 (0.625 - 1.706)	1.38 (0.680 - 2.800)	0.814 (0.510 - 1.297)	0.829 (0.634 - 1.084)	1.075 (0.786 - 1.470)	0.756 (0.491 - 1.165)	0.954 (0.776 - 1.171)
Diabetes											
Nonstandard	0.892 (0.763 - 1.043)	0.948 (0.755 - 1.190)	0.840 (0.689 - 1.024)	0.862 (0.712 - 1.042)	0.995 (0.726 - 1.366)	0.669 (0.425 - 1.051)	0.998 (0.767 - 1.297)	0.789** (0.640 - 0.973)	1.011 (0.720 - 1.420)	0.809 (0.568 - 1.152)	0.913 (0.754 - 1.106)
Irregular	1.01 (0.815 - 1.251)	0.829 (0.603 - 1.139)	1.12 (0.866 - 1.448)	0.994 (0.763 - 1.294)	1.032 (0.697 - 1.527)	0.981 (0.570 - 1.688)	0.912 (0.603 - 1.378)	0.957 (0.710 - 1.289)	1.139 (0.804 - 1.613)	1.076 (0.660 - 1.752)	0.991 (0.784 - 1.253)
Hypertension											
Nonstandard	0.855** (0.741 - 0.986)	0.860 (0.726 - 1.019)	0.839 (0.658 - 1.070)	0.850 (0.709 - 1.020)	0.938 (0.710 - 1.238)	0.996 (0.578 - 1.716)	0.887 (0.652 - 1.207)	0.867 (0.707 - 1.063)	0.747 (0.546 - 1.021)	0.811 (0.612 - 1.075)	0.859 (0.727 - 1.015)
Irregular	0.803** (0.655 - 0.984)	0.871 (0.652 - 1.163)	0.747** (0.560 - 0.996)	0.675*** (0.531 - 0.858)	1.653** (1.100 - 2.483)	1.469 (0.687 - 3.142)	0.655 (0.397 - 1.081)	0.744** (0.559 - 0.991)	0.935 (0.686 - 1.274)	0.894 (0.588 - 1.359)	0.782 (0.611 - 1.001)
High Inflammation											
Nonstandard	0.951 (0.832 - 1.088)	0.983 (0.818 - 1.181)	0.936 (0.762 - 1.150)	0.88 (0.752 - 1.029)	1.227 (0.964 - 1.560)	0.954 (0.568 - 1.603)	1.102 (0.845 - 1.435)	0.9 (0.749 - 1.080)	0.83 (0.633 - 1.088)	0.636*** (0.470 - 0.861)	1.078 (0.925 - 1.256)
Irregular	0.931 (0.775 - 1.118)	0.767** (0.601 - 0.979)	1.078 (0.839 - 1.386)	0.825 (0.665 - 1.024)	1.332 (0.866 - 2.049)	1.506 (0.834 - 2.720)	1.028 (0.653 - 1.617)	0.942 (0.706 - 1.256)	0.865 (0.609 - 1.230)	0.734 (0.440 - 1.224)	0.976 (0.791 - 1.206)

Note: Referent group = standard work schedule; Control variables include sex, education, race/ethnicity, occupational industry, marital status, smoking status, supervisor role, number of worked hours per week, and length of employment.
*** p<0.01, ** p<0.05.

Table 3.4. Weighted multivariate logistic regression models examining the association between work schedules at young adulthood (wave 4) and dichotomous CVH outcomes at early mid-life (wave 5), controlling for sociodemographic and health risk factors. Presented as odds ratios with 95% confidence intervals.

	Full Sample	Female	Male	White	Black	Hispanic	Highschool or less	Some College	BA+	Service Sector	Other Industry
Obesity											
Nonstandard	1.220** (1.010 - 1.474)	1.468*** (1.117 - 1.929)	0.977 (0.707 - 1.349)	1.053 (0.856 - 1.295)	2.247*** (1.313 - 3.846)	1.24 (0.670 - 2.295)	1.254 (0.824 - 1.909)	1.331 (0.973 - 1.819)	0.954 (0.686 - 1.326)	1.103 (0.731 - 1.662)	1.333** (1.041 - 1.706)
Irregular	1.047 (0.795 - 1.378)	0.768 (0.536 - 1.101)	1.431 (0.939 - 2.181)	1.03 (0.748 - 1.418)	1.04 (0.489 - 2.215)	1.147 (0.396 - 3.320)	0.969 (0.385 - 2.440)	1.085 (0.692 - 1.702)	0.964 (0.632 - 1.469)	0.81 (0.371 - 1.770)	1.184 (0.873 - 1.605)
Diabetes											
Nonstandard	1.276 (0.957 - 1.702)	1.445 (0.996 - 2.098)	1.027 (0.634 - 1.662)	1.32 (0.903 - 1.932)	1.142 (0.734 - 1.775)	1.438 (0.439 - 4.713)	1.519 (0.847 - 2.724)	1.167 (0.757 - 1.797)	1.141 (0.679 - 1.919)	1.244 (0.687 - 2.252)	1.201 (0.843 - 1.712)
Irregular	1.058 (0.682 - 1.643)	1.171 (0.690 - 1.987)	0.896 (0.446 - 1.798)	0.881 (0.533 - 1.457)	1.618 (0.708 - 3.699)	1.053 (0.173 - 6.405)	1.859 (0.616 - 5.612)	0.965 (0.527 - 1.768)	0.799 (0.404 - 1.580)	1.34 (0.545 - 3.294)	0.953 (0.547 - 1.661)
Hypertension											
Nonstandard	1.052 (0.864 - 1.281)	1.204 (0.947 - 1.531)	0.863 (0.603 - 1.236)	1.052 (0.838 - 1.323)	1.425 (0.859 - 2.363)	1.032 (0.448 - 2.375)	0.935 (0.552 - 1.582)	1.193 (0.885 - 1.609)	0.915 (0.682 - 1.226)	1.013 (0.696 - 1.474)	1.084 (0.823 - 1.428)
Irregular	0.812 (0.602 - 1.096)	0.571*** (0.379 - 0.859)	1.302 (0.824 - 2.056)	0.799 (0.556 - 1.148)	1.306 (0.505 - 3.374)	0.638 (0.215 - 1.893)	0.521 (0.223 - 1.219)	0.833 (0.548 - 1.267)	0.862 (0.556 - 1.335)	0.602 (0.318 - 1.138)	0.914 (0.660 - 1.266)
High Inflammation											
Nonstandard	1.145 (0.946 - 1.386)	1.001 (0.770 - 1.301)	1.349 (0.968 - 1.879)	0.998 (0.783 - 1.271)	1.638** (1.067 - 2.512)	1.32 (0.566 - 3.078)	1.465 (0.934 - 2.300)	1.218 (0.902 - 1.646)	0.803 (0.531 - 1.213)	0.761 (0.506 - 1.144)	1.311** (1.034 - 1.663)
Irregular	1.001 (0.721 - 1.391)	0.941 (0.624 - 1.419)	1.079 (0.654 - 1.778)	1.027 (0.704 - 1.499)	0.981 (0.447 - 2.153)	0.717 (0.145 - 3.536)	0.991 (0.401 - 2.448)	1.304 (0.781 - 2.178)	0.775 (0.503 - 1.195)	1.08 (0.526 - 2.221)	0.929 (0.656 - 1.315)
High LDL-Cholesterol											
Nonstandard	1.083 (0.810 - 1.449)	1.198 (0.787 - 1.826)	0.994 (0.672 - 1.469)	1.049 (0.721 - 1.526)	0.555 (0.261 - 1.181)	1.882 (0.813 - 4.356)	1.334 (0.660 - 2.695)	1.241 (0.797 - 1.932)	0.781 (0.474 - 1.288)	1.471 (0.800 - 2.704)	1.005 (0.711 - 1.421)
Irregular	0.854	1.011	0.743	0.749	1.241	0.59	1.468	1.459	0.457**	1.827	0.666

	(0.562 - 1.299)	(0.565 - 1.808)	(0.409 - 1.352)	(0.458 - 1.225)	(0.313 - 4.924)	(0.149 - 2.330)	(0.325 - 6.636)	(0.790 - 2.695)	(0.233 - 0.899)	(0.663 - 5.036)	(0.400 - 1.108)

Note: Referent group = standard work schedule; Control variables include sex, education, race/ethnicity, occupational industry, marital status, smoking status.
*** p<0.01, ** p<0.05.

Appendix C

Table C.1. Sample characteristics of workers with standard, nonstandard, and irregular work schedules at wave 4 and wave 5. Presented as weighted proportions.

	Wave 4			Wave 5		
	Standard Schedules N=10,130 (67.2)	*Nonstandard Schedules N=3,439 (22.9)*	*Irregular Schedules N=1,420 (10.0)*	*Standard Schedules N=3,412 (66.2)*	*Nonstandard Schedules N=1,096 (21.9)*	*Irregular Schedules N=502 (10.1)*
Race						
White	71.3	68.7	77.1	73.5	68.9	77.8
Black	14.7	20.5	11.0	14.2	20.6	10.9
Hispanic	9.7	7.2	7.5	8.8	8.1	8.6
Other	4.4	3.6	4.4	3.6	2.4	2.6
Education						
High School or less	25.2	32.1	18.5	15.5	24.8	11.9
Some College	40.7	50.9	45.3	37.6	48.4	37.7
BA+	34.2	17.0	36.2	46.9	26.8	50.4
Married	51.5	46.9	47.7	60.6	52.1	53.8
Gender						
Female	51.0	51.6	41.3	56.2	51.3	50.8
Male	49.0	48.4	58.7	43.8	48.7	49.2
Service Industry Workers	13.6	34.8	21.3	13.8	35.1	23.1
Smoker	22.5	30.7	27.2	22.4	33.9	25.6
BMI						
Obese	36.3	39.1	33.9	45.5	53.8	45.7
Overweight	30.0	28.3	31.8	29.4	24.4	23.9
Normal or Underweight	33.7	32.5	34.3	25.1	21.8	30.4
Glycated hemoglobin (HbA1c)						
Diabetes	3.3	4.3	3.9	4.2	5.7	6.1
Prediabetes	27.3	27.0	26.3	7.1	10.0	4.9
No Diabetes	69.4	68.7	70.0	88.8	84.2	89
Blood Pressure						
Hypertension	19.5	19.5	17.7	19.3	22.1	24.2
Pre-Hypertension	48.5	47.0	49.7	42.3	44.8	34.3
No Hypertension	32.0	33.5	32.6	38.5	33.1	41.4
High Inflammation	40.8	40.8	36.9	35.2	40.8	33.9
High Cholesterol	-	-	-	21.8	24.1	19.9

Table C.2. Predicted Probabilities based on logistic regression models for full sample of workers at young adulthood and each indicator of CVH.

	Obesity		**Diabetes**		**Hypertension**		**High Inflammation**	
	Predicted Probabilities	***CI***	***Predicted Probabilities***	***CI***	***Predicted Probabilities***	***CI***	***Predicted Probabilities***	***CI***
Standard Workers	36.7	35.1-38.2	31.8	30.1-33.6	69.7	68.3-71.1	39.6	38.0-41.3
Nonstandard Workers	36.8	33.8-39.8	29.6	27.1-32.1	66.7	63.9-69.4	38.5	35.5-41.5
Irregular Workers	34.8	30.8-38.8	32.0	28.1-35.9	65.4	61.8-69.0	38.0	34.1-41.9

Note: CI = confidence intervals

Table C.3. Predicted Probabilities based on logistic regression models for full sample of workers at early mid-life and each indicator of CVH.

	Obesity		**Diabetes**		**Hypertension**		**High Inflammation**		**High LDL-Cholesterol**	
	Predicted Probabilities	***CI***	***Predicted Probabilities***	***CI***	***Predicted Probabilities***	***CI***	***Predicted Probabilities***	***CI***	***Predicted Probabilities***	***CI***
Standard Workers	46.3	43.8-48.8	11.6	10.1-13.1	62.7	60.4-64.9	35.7	33.5-37.9	22.1	19.9-24.2
Nonstandard Workers	51.0	47.0-55.1	14.2	11.3-17.0	63.8	59.8-67.7	38.7	34.8-42.6	23.4	19.0-27.8
Irregular Workers	47.4	41.0-53.7	12.1	7.8-16.5	58.2	51.9-64.6	35.7	29.1-42.4	19.5	13.3-25.7

Note: CI = confidence intervals

Table C.4. Weighted multivariate logistic regression models with all controls, examining the association between work hours and obesity at young adulthood (wave 4) and controlling for sociodemographic and health risk factors. Presented as odds ratios with 95% confidence intervals.

	Full Sample	Female	Male	White	Black	Hispanic	HS or Less	Some College	BA+	Service Industry	Other Industry
Nonstandard	1.005 (0.876 - 1.154)	0.933 (0.763 - 1.140)	1.061 (0.875 - 1.286)	0.99 (0.830 - 1.180)	1.206 (0.915 - 1.590)	0.986 (0.666 - 1.461)	1.103 (0.844 - 1.441)	0.966 (0.799 - 1.167)	0.862 (0.656 - 1.133)	0.752 (0.551 - 1.026)	1.076 (0.921 - 1.258)
Irregular	0.919 (0.758 - 1.115)	0.901 (0.651 - 1.246)	0.936 (0.722 - 1.214)	0.862 (0.700 - 1.062)	1.033 (0.625 - 1.706)	1.38 (0.680 - 2.800)	0.814 (0.510 - 1.297)	0.829 (0.634 - 1.084)	1.075 (0.786 - 1.470)	0.756 (0.491 - 1.165)	0.954 (0.776 - 1.171)
Female	1.100 (0.982 - 1.231)			0.984 (0.870 - 1.113)	2.023*** (1.509 - 2.712)	1.182 (0.781 - 1.789)	1.659*** (1.313 - 2.096)	1.018 (0.862 - 1.203)	0.88 (0.718 - 1.079)	1.185 (0.898 - 1.564)	1.08 (0.951 - 1.227)
Some College	0.959 (0.830 - 1.109)	0.722*** (0.594 - 0.877)	1.102 (0.896 - 1.356)	0.984 (0.823 - 1.176)	0.895 (0.607 - 1.320)	0.956 (0.597 - 1.531)				0.822 (0.620 - 1.089)	0.986 (0.834 - 1.165)
BA+	0.519*** (0.440 - 0.612)	0.385*** (0.306 - 0.484)	0.625*** (0.501 - 0.780)	0.491*** (0.395 - 0.609)	0.748 (0.515 - 1.087)	0.525** (0.304 - 0.906)				0.380*** (0.258 - 0.561)	0.547*** (0.451 - 0.665)
Black	1.515*** (1.343 - 1.709)	2.183*** (1.819 - 2.619)	1.049 (0.861 - 1.277)				1.255 (0.903 - 1.745)	1.301** (1.041 - 1.626)	2.394*** (1.827 - 3.135)	1.234 (0.871 - 1.749)	1.568*** (1.370 - 1.795)
Hispanic	1.175 (0.982 - 1.405)	1.322 (0.990 - 1.765)	1.052 (0.791 - 1.398)				1.08 (0.710 - 1.641)	1.124 (0.852 - 1.483)	1.281 (0.913 - 1.796)	1.188 (0.676 - 2.090)	1.188* (0.983 - 1.437)
Other	0.773 (0.508 - 1.174)	0.565 (0.305 - 1.044)	0.953 (0.643 - 1.412)				1.229 (0.565 - 2.672)	0.655* (0.399 - 1.077)	0.635* (0.394 - 1.024)	0.503* (0.238 - 1.065)	0.831 (0.530 - 1.301)
Married	1.073 (0.970 - 1.186)	0.999 (0.857 - 1.165)	1.148 (0.981 - 1.343)	1.022 (0.911 - 1.146)	1.228 (0.977 - 1.542)	1.294 (0.961 - 1.741)	1.112 (0.868 - 1.424)	0.956 (0.804 - 1.135)	1.230** (1.035 - 1.462)	0.816 (0.616 - 1.082)	1.123** (1.011 - 1.248)
Supervisor	1.017 (0.884 - 1.170)	1.027 (0.852 - 1.237)	1.002 (0.834 - 1.204)	1.043 (0.866 - 1.257)	1.041 (0.824 - 1.315)	0.857 (0.634 - 1.159)	1.067 (0.847 - 1.344)	0.978 (0.808 - 1.183)	1.038 (0.833 - 1.295)	1.441*** (1.104 - 1.881)	0.951 (0.817 - 1.108)
Total Jobs	1.249** (1.028 - 1.518)	1.088 (0.813 - 1.456)	1.400** (1.079 - 1.815)	1.246 (0.966 - 1.606)	1.07 (0.776 - 1.476)	1.262 (0.741 - 2.150)	1.127 (0.689 - 1.845)	1.216 (0.924 - 1.600)	1.413 (0.999 - 1.999)	1.362 (0.837 - 2.219)	1.241** (1.019 - 1.511)
Working Years	1.007 (0.987 - 1.027)	0.995 (0.966 - 1.025)	1.015 (0.986 - 1.044)	0.997 (0.975 - 1.019)	1.040 (0.994 - 1.089)	1.023 (0.974 - 1.074)	1.003 (0.965 - 1.042)	1.003 (0.977 - 1.029)	1.026 (0.984 - 1.071)	0.985 (0.938 - 1.036)	1.011 (0.992 - 1.032)
Smoker	0.753*** (0.642 -	0.967 (0.767 -	0.639*** (0.527 -	0.734*** (0.612 -	0.772 (0.581 -	0.779 (0.404 -	0.692*** (0.553 -	0.673*** (0.542 -	1.298 (0.912 -	0.735* (0.534 -	0.758*** (0.636 -

	0.883)	1.219)	0.776)	0.880)	1.027)	1.505)	0.865)	0.835)	1.849)	1.013)	0.904)
Constant	0.628***	0.876	0.572***	0.719***	0.520***	0.626	0.562***	0.751**	0.283***	0.87	0.592***
	(0.513 - 0.769)	(0.652 - 1.175)	(0.443 - 0.738)	(0.568 - 0.910)	(0.357 - 0.756)	(0.355 - 1.103)	(0.401 - 0.789)	(0.583 - 0.967)	(0.214 - 0.375)	(0.556 - 1.361)	(0.474 - 0.740)

Note: Referent group = standard work schedule; Control variables include sex, education, race/ethnicity, occupational industry, marital status, smoking status, supervisor role, number of worked hours per week, and length of employment.
*** p<0.01, ** p<0.05.

Table C.5. Fully controlled weighted multivariate logistic regression models examining the association between work hours and diabetes at young adulthood (wave 4), controlling for sociodemographic and health risk factors. Presented as odds ratios with 95% confidence intervals.

	Full Sample	Female	Male	White	Black	Hispanic	HS or Less	Some College	BA+	Service Industry	Other Industry
Nonstandard	0.892	0.948	0.840	0.862	0.995	0.669*	0.998	0.789**	1.011	0.809	0.913
	(0.763 - 1.043)	(0.755 - 1.190)	(0.689 - 1.024)	(0.712 - 1.042)	(0.726 - 1.366)	(0.425 - 1.051)	(0.767 - 1.297)	(0.640 - 0.973)	(0.720 - 1.420)	(0.568 - 1.152)	(0.754 - 1.106)
Irregular	1.01	0.829	1.12	0.994	1.032	0.981	0.912	0.957	1.139	1.076	0.991
	(0.815 - 1.251)	(0.603 - 1.139)	(0.866 - 1.448)	(0.763 - 1.294)	(0.697 - 1.527)	(0.570 - 1.688)	(0.603 - 1.378)	(0.710 - 1.289)	(0.804 - 1.613)	(0.660 - 1.752)	(0.784 - 1.253)
Female	0.580***			0.580***	0.616***	0.553***	0.748**	0.523***	0.538***	0.621***	0.561***
	(0.508 - 0.662)			(0.489 - 0.688)	(0.493 - 0.770)	(0.398 - 0.768)	(0.573 - 0.975)	(0.432 - 0.633)	(0.416 - 0.697)	(0.465 - 0.830)	(0.484 - 0.650)
Some College	0.907	0.723**	1.022	0.857	0.893	1.222				0.554***	1.027
	(0.774 - 1.062)	(0.549 - 0.953)	(0.845 - 1.236)	(0.687 - 1.068)	(0.665 - 1.200)	(0.781 - 1.911)				(0.406 - 0.756)	(0.852 - 1.239)
BA+	0.564***	0.481***	0.600***	0.507***	0.791	0.534**				0.320***	0.637***
	(0.463 - 0.689)	(0.360 - 0.641)	(0.470 - 0.764)	(0.390 - 0.659)	(0.573 - 1.093)	(0.327 - 0.873)				(0.205 - 0.501)	(0.511 - 0.794)
Black	4.576***	4.815***	4.292***				3.340***	4.313***	7.327***	3.495***	4.834***
	(3.802 - 5.509)	(3.811 - 6.085)	(3.373 - 5.462)				(2.350 - 4.749)	(3.489 - 5.333)	(5.607 - 9.575)	(2.591 - 4.716)	(3.928 - 5.947)
Hispanic	1.770***	1.817***	1.749***				1.316	2.064***	1.653**	1.433	1.853***
	(1.498 - 2.090)	(1.384 - 2.384)	(1.402 - 2.182)				(0.901 - 1.923)	(1.570 - 2.713)	(1.122 - 2.434)	(0.888 - 2.312)	(1.543 - 2.225)
Other	1.862***	1.412	2.266***				1.509	1.743*	2.299***	1.201	2.007***
	(1.206 - 2.877)	(0.801 - 2.487)	(1.433 - 3.582)				(0.805 - 2.829)	(0.980 - 3.101)	(1.385 - 3.818)	(0.694 - 2.080)	(1.222 - 3.299)
Married	1.044	0.912	1.158*	1.048	1.12	0.883	1.075	0.973	1.119	0.87	1.073
	(0.926 - 1.178)	(0.738 - 1.125)	(0.993 - 1.351)	(0.898 - 1.222)	(0.914 - 1.374)	(0.639 - 1.220)	(0.813 - 1.422)	(0.826 - 1.145)	(0.924 - 1.356)	(0.637 - 1.190)	(0.942 - 1.221)
Supervisor	0.931	0.996	0.883	0.893	0.972	1.118	0.961	0.971	0.816	0.805	0.96
	(0.817 - 1.061)	(0.824 - 1.204)	(0.743 - 1.049)	(0.754 - 1.058)	(0.735 - 1.286)	(0.784 - 1.593)	(0.741 - 1.247)	(0.799 - 1.180)	(0.626 - 1.065)	(0.574 - 1.128)	(0.842 - 1.095)
Total Jobs	1.198	1.399***	1.069	1.278	0.988	1.101	1.031	1.282	1.163	1.553*	1.151
	(0.990 - 1.449)	(1.086 - 1.802)	(0.817 - 1.397)	(0.990 - 1.651)	(0.667 - 1.464)	(0.520 - 2.332)	(0.609 - 1.746)	(0.945 - 1.741)	(0.812 - 1.666)	(0.964 - 2.502)	(0.921 - 1.438)
Working Years	1.006	1.01	1.002	1.014	0.972	0.999	0.994	1.005	1.03	1.045*	0.998
	(0.986 - 1.028)	(0.977 - 1.043)	(0.973 - 1.032)	(0.987 - 1.042)	(0.926 - 1.019)	(0.937 - 1.065)	(0.960 - 1.029)	(0.976 - 1.034)	(0.978 - 1.084)	(0.993 - 1.100)	(0.976 - 1.022)
Smoker	0.985	1.043	0.956	1.13	0.491***	0.495***	0.796	1.051	1.226	0.789	1.037
	(0.843 -	(0.826 -	(0.782 -	(0.946 -	(0.329 -	(0.294 -	(0.620 -	(0.857 -	(0.816 -	(0.576 -	(0.867 -

	1.151)	1.317)	1.168)	1.349)	0.733)	0.834)	1.021)	1.288)	1.842)	1.081)	1.240)
Constant	0.511*** (0.417 - 0.626)	0.351*** (0.241 - 0.511)	0.485*** (0.376 - 0.626)	0.511*** (0.393 - 0.666)	2.558*** (1.967 - 3.327)	0.953 (0.572 - 1.587)	0.573*** (0.412 - 0.797)	0.503*** (0.406 - 0.624)	0.244*** (0.179 - 0.334)	0.803 (0.516 - 1.250)	0.463*** (0.364 - 0.588)

Note: Referent group = standard work schedule; Control variables include sex, education, race/ethnicity, occupational industry, marital status, smoking status, supervisor role, number of worked hours per week, and length of employment.
*** p<0.01, ** p<0.05.

Table C.6. Fully controlled weighted multivariate logistic regression models examining the association between work hours and hypertension at young adulthood (wave 4), controlling for sociodemographic and health risk factors. Presented as odds ratios with 95% confidence intervals.

	Full Sample	Female	Male	White	Black	Hispanic	HS or Less	Some College	BA+	Service Industry	Other Industry
Nonstandard	0.855**	0.860	0.839	0.850	0.938	0.996	0.887	0.867	0.747	0.811	0.859
	(0.741 - 0.986)	(0.726 - 1.019)	(0.658 - 1.070)	(0.709 - 1.020)	(0.710 - 1.238)	(0.578 - 1.716)	(0.652 - 1.207)	(0.707 - 1.063)	(0.546 - 1.021)	(0.612 - 1.075)	(0.727 - 1.015)
Irregular	0.803**	0.871	0.747**	0.675***	1.653**	1.469	0.655	0.744**	0.935	0.894	0.782
	(0.655 - 0.984)	(0.652 - 1.163)	(0.560 - 0.996)	(0.531 - 0.858)	(1.100 - 2.483)	(0.687 - 3.142)	(0.397 - 1.081)	(0.559 - 0.991)	(0.686 - 1.274)	(0.588 - 1.359)	(0.611 - 1.001)
Female	0.224***			0.202***	0.315***	0.225***	0.251***	0.228***	0.197***	0.252***	0.216***
	(0.198 - 0.253)			(0.177 - 0.230)	(0.237 - 0.418)	(0.136 - 0.370)	(0.189 - 0.334)	(0.192 - 0.271)	(0.164 - 0.237)	(0.183 - 0.348)	(0.190 - 0.245)
Some College	0.851**	0.802**	0.885	0.893	0.718*	0.872				0.858	0.842
	(0.734 - 0.988)	(0.662 - 0.973)	(0.702 - 1.116)	(0.741 - 1.075)	(0.489 - 1.056)	(0.539 - 1.411)				(0.579 - 1.270)	(0.707 - 1.003)
BA+	0.698***	0.644***	0.779	0.755***	0.614**	0.589				0.793	0.677***
	(0.604 - 0.807)	(0.526 - 0.788)	(0.598 - 1.015)	(0.636 - 0.896)	(0.407 - 0.924)	(0.344 - 1.010)				(0.513 - 1.226)	(0.568 - 0.807)
Black	1.077	1.279***	0.803				1.122	1.035	1.127	1.232	1.052
	(0.915 - 1.268)	(1.079 - 1.516)	(0.585 - 1.103)				(0.716 - 1.756)	(0.829 - 1.293)	(0.845 - 1.503)	(0.827 - 1.836)	(0.877 - 1.262)
Hispanic	0.958	1.005	0.891				0.898	1.016	0.813	0.85	0.975
	(0.778 - 1.180)	(0.764 - 1.324)	(0.602 - 1.319)				(0.580 - 1.390)	(0.751 - 1.374)	(0.576 - 1.147)	(0.519 - 1.392)	(0.782 - 1.217)
Other	0.783	0.913	0.650**				1.128	0.762	0.654**	0.948	0.741*
	(0.569 - 1.076)	(0.640 - 1.301)	(0.428 - 0.988)				(0.507 - 2.510)	(0.430 - 1.348)	(0.440 - 0.973)	(0.533 - 1.686)	(0.525 - 1.046)
Married	0.91	0.903	0.93	0.866**	1.041	1.038	1.246	0.859*	0.813**	0.612***	0.984
	(0.811 - 1.020)	(0.776 - 1.053)	(0.752 - 1.150)	(0.755 - 0.993)	(0.793 - 1.367)	(0.725 - 1.486)	(0.925 - 1.676)	(0.720 - 1.025)	(0.682 - 0.970)	(0.456 - 0.820)	(0.869 - 1.115)
Supervisor	1.046	1.089	0.987	1.019	0.918	1.198	1.233	0.993	1.01	1.421**	0.982
	(0.924 - 1.185)	(0.937 - 1.264)	(0.802 - 1.215)	(0.877 - 1.185)	(0.676 - 1.246)	(0.847 - 1.694)	(0.894 - 1.701)	(0.820 - 1.203)	(0.845 - 1.207)	(1.065 - 1.896)	(0.858 - 1.125)
Total Jobs	0.97	1.018	0.897	1.011	0.948	0.811	0.908	0.998	0.931	0.697	1.035
	(0.782 - 1.203)	(0.801 - 1.295)	(0.632 - 1.272)	(0.776 - 1.317)	(0.590 - 1.523)	(0.363 - 1.814)	(0.484 - 1.704)	(0.749 - 1.331)	(0.643 - 1.349)	(0.421 - 1.151)	(0.834 - 1.285)
Working Years	0.995	1.001	0.987	0.981	1.049	1.02	0.973	1.004	1.003	1.014	0.989
	(0.973 - 1.017)	(0.975 - 1.027)	(0.953 - 1.021)	(0.954 - 1.009)	(0.994 - 1.107)	(0.967 - 1.076)	(0.936 - 1.011)	(0.976 - 1.032)	(0.963 - 1.046)	(0.967 - 1.064)	(0.965 - 1.012)
Smoker	0.922	1.047	0.804	0.992	0.599**	0.739	0.713**	0.935	1.479**	1.331	0.844
	(0.770 -	(0.814 -	(0.634 -	(0.817 -	(0.392 -	(0.366 -	(0.509 -	(0.731 -	(1.035 -	(0.935 -	(0.698 -

	1.104)	1.347)	1.020)	1.204)	0.915)	1.491)	0.999)	1.196)	2.114)	1.894)	1.020)
Constant	6.814*** (5.535 - 8.389)	1.451*** (1.136 - 1.852)	7.639*** (5.402 - 10.802)	7.592*** (6.020 - 9.574)	5.369*** (3.170 - 9.094)	5.131*** (2.431 - 10.832)	6.320*** (4.285 - 9.320)	5.792*** (4.514 - 7.431)	5.267*** (4.157 - 6.674)	5.448*** (2.837 - 10.464)	7.317*** (5.932 - 9.026)

Note: Referent group = standard work schedule; Control variables include sex, education, race/ethnicity, occupational industry, marital status, smoking status, supervisor role, number of worked hours per week, and length of employment.
*** p<0.01, ** p<0.05.

Table C.7. Fully controlled weighted multivariate logistic regression models examining the association between work hours and high inflammation at young adulthood (wave 4), controlling for sociodemographic and health risk factors. Presented as odds ratios with 95% confidence intervals.

	Full Sample	Female	Male	White	Black	Hispanic	HS or Less	Some College	BA+	Service Industry	Other Industry
Nonstandard	0.951 (0.832 - 1.088)	0.983 (0.818 - 1.181)	0.936 (0.762 - 1.150)	0.88 (0.752 - 1.029)	1.227 (0.964 - 1.560)	0.954 (0.568 - 1.603)	1.102 (0.845 - 1.435)	0.9 (0.749 - 1.080)	0.83 (0.633 - 1.088)	0.636*** (0.470 - 0.861)	1.078 (0.925 - 1.256)
Irregular	0.931 (0.775 - 1.118)	0.767** (0.601 - 0.979)	1.078 (0.839 - 1.386)	0.825 (0.665 - 1.024)	1.332 (0.866 - 2.049)	1.506 (0.834 - 2.720)	1.028 (0.653 - 1.617)	0.942 (0.706 - 1.256)	0.865 (0.609 - 1.230)	0.734 (0.440 - 1.224)	0.976 (0.791 - 1.206)
Female	2.356*** (2.084 - 2.664)			2.282*** (1.970 - 2.644)	2.976*** (2.282 - 3.882)	2.424*** (1.832 - 3.206)	2.542*** (1.921 - 3.364)	2.146*** (1.834 - 2.511)	2.541*** (2.048 - 3.153)	2.607*** (1.986 - 3.423)	2.338*** (2.039 - 2.682)
Some College	0.896 (0.775 - 1.035)	0.790** (0.638 - 0.978)	0.993 (0.814 - 1.212)	0.872 (0.731 - 1.042)	0.852 (0.670 - 1.084)	1.36 (0.941 - 1.966)				0.746** (0.572 - 0.972)	0.922 (0.778 - 1.093)
BA+	0.685*** (0.577 - 0.813)	0.642*** (0.508 - 0.812)	0.687*** (0.527 - 0.896)	0.631*** (0.509 - 0.782)	0.9 (0.647 - 1.251)	1.03 (0.631 - 1.682)				0.558*** (0.365 - 0.852)	0.705*** (0.581 - 0.855)
Black	1.203* (0.984 - 1.471)	1.297** (1.002 - 1.677)	1.071 (0.848 - 1.352)				1.143 (0.834 - 1.567)	1.062 (0.850 - 1.327)	1.585*** (1.125 - 2.232)	1.269 (0.857 - 1.881)	1.176 (0.959 - 1.443)
Hispanic	1.073 (0.909 - 1.267)	1.132 (0.903 - 1.418)	1.014 (0.799 - 1.288)				0.777 (0.570 - 1.059)	1.174 (0.904 - 1.524)	1.305 (0.862 - 1.978)	1.758** (1.100 - 2.812)	0.994 (0.823 - 1.201)
Other	0.599*** (0.408 - 0.881)	0.499*** (0.332 - 0.749)	0.729 (0.426 - 1.248)				1.084 (0.429 - 2.736)	0.442*** (0.302 - 0.648)	0.552*** (0.360 - 0.848)	0.699 (0.251 - 1.943)	0.574*** (0.413 - 0.796)
Married	0.983 (0.876 - 1.104)	0.959 (0.813 - 1.131)	1.02 (0.856 - 1.215)	0.963 (0.840 - 1.103)	0.923 (0.702 - 1.215)	1.22 (0.817 - 1.823)	1.200* (0.985 - 1.462)	0.783*** (0.658 - 0.932)	1.157 (0.930 - 1.438)	0.793 (0.607 - 1.037)	1.005 (0.881 - 1.147)
Supervisor	1.012 (0.899 - 1.140)	1.08 (0.903 - 1.291)	0.934 (0.780 - 1.118)	1.018 (0.878 - 1.181)	1.18 (0.911 - 1.528)	0.866 (0.642 - 1.169)	0.904 (0.697 - 1.172)	1.065 (0.896 - 1.266)	1.029 (0.829 - 1.278)	1.341 (0.982 - 1.830)	0.971 (0.856 - 1.102)
Total Jobs	0.917 (0.746 - 1.127)	0.935 (0.733 - 1.192)	0.899 (0.647 - 1.249)	0.933 (0.716 - 1.215)	0.935 (0.685 - 1.276)	0.756 (0.414 - 1.383)	0.619** (0.389 - 0.986)	0.999 (0.727 - 1.372)	1.011 (0.755 - 1.354)	0.89 (0.512 - 1.548)	0.922 (0.727 - 1.169)
Working Years	0.997 (0.977 - 1.017)	0.986 (0.960 - 1.012)	1.004 (0.976 - 1.033)	0.991 (0.969 - 1.013)	1.033 (0.975 - 1.096)	0.979 (0.926 - 1.035)	0.989 (0.952 - 1.028)	1.006 (0.978 - 1.035)	0.985 (0.939 - 1.033)	0.952* (0.906 - 1.002)	1.004 (0.983 - 1.025)
Smoker	0.926 (0.810 -	0.758*** (0.616 -	1.1 (0.899 -	0.923 (0.789 -	1.002 (0.711 -	0.553* (0.288 -	1.074 (0.807 -	0.822 (0.668 -	0.9 (0.616 -	1.036 (0.766 -	0.913 (0.784 -

	1.059)	0.931)	1.345)	1.079)	1.414)	1.060)	1.430)	1.011)	1.315)	1.400)	1.062)
Constant	0.520*** (0.416 - 0.650)	1.431** (1.073 - 1.908)	0.470*** (0.349 - 0.634)	0.585*** (0.455 - 0.751)	0.399*** (0.285 - 0.558)	0.429*** (0.275 - 0.669)	0.471*** (0.315 - 0.703)	0.550*** (0.428 - 0.707)	0.319*** (0.228 - 0.446)	0.657 (0.410 - 1.054)	0.501*** (0.392 - 0.640)

Note: Referent group = standard work schedule; Control variables include sex, education, race/ethnicity, occupational industry, marital status, smoking status, supervisor role, number of worked hours per week, and length of employment.
*** p<0.01, ** p<0.05.

Table C.8. Fully controlled weighted multivariate logistic regression models examining the association between work hours at young adulthood (wave 4) and obesity at early mid-life (wave 5), controlling for sociodemographic and health risk factors. Presented as odds ratios with 95% confidence intervals.

	Full Sample	**Female**	**Male**	**White**	**Black**	**Hispanic**	**HS or Less**	**Some College**	**BA+**	**Service Industry**	**Other Industry**
Nonstandard	1.220** (1.010 - 1.474)	1.468*** (1.117 - 1.929)	0.977 (0.707 - 1.349)	1.053 (0.856 - 1.295)	2.247*** (1.313 - 3.846)	1.24 (0.670 - 2.295)	1.254 (0.824 - 1.909)	1.331* (0.973 - 1.819)	0.954 (0.686 - 1.326)	1.103 (0.731 - 1.662)	1.333** (1.041 - 1.706)
Irregular	1.047 (0.795 - 1.378)	0.768 (0.536 - 1.101)	1.431* (0.939 - 2.181)	1.03 (0.748 - 1.418)	1.04 (0.489 - 2.215)	1.147 (0.396 - 3.320)	0.969 (0.385 - 2.440)	1.085 (0.692 - 1.702)	0.964 (0.632 - 1.469)	0.81 (0.371 - 1.770)	1.184 (0.873 - 1.605)
Female	1.103 (0.899 - 1.353)			1.005 (0.791 - 1.277)	2.216*** (1.377 - 3.565)	1.019 (0.553 - 1.876)	1.821** (1.140 - 2.907)	1.132 (0.851 - 1.505)	0.883 (0.667 - 1.169)	1.047 (0.669 - 1.639)	1.127 (0.903 - 1.408)
Some College	0.913 (0.721 - 1.157)	0.700* (0.479 - 1.021)	1.047 (0.747 - 1.469)	0.99 (0.727 - 1.347)	0.956 (0.536 - 1.706)	0.568 (0.247 - 1.308)				0.829 (0.520 - 1.323)	0.95 (0.721 - 1.253)
BA+	0.501*** (0.392 - 0.639)	0.380*** (0.267 - 0.541)	0.609*** (0.425 - 0.872)	0.527*** (0.386 - 0.719)	0.66 (0.349 - 1.246)	0.389** (0.189 - 0.801)				0.323*** (0.189 - 0.552)	0.547*** (0.406 - 0.736)
Black	1.736*** (1.335 - 2.256)	2.326*** (1.676 - 3.227)	1.303 (0.892 - 1.903)				1.756* (0.964 - 3.198)	1.607** (1.062 - 2.432)	2.003*** (1.363 - 2.944)	2.291*** (1.347 - 3.897)	1.606*** (1.210 - 2.132)
Hispanic	1.392** (1.049 - 1.847)	1.335 (0.911 - 1.954)	1.470* (0.949 - 2.278)				1.997* (0.948 - 4.206)	1.174 (0.761 - 1.811)	1.342 (0.840 - 2.145)	1.148 (0.611 - 2.155)	1.389** (1.010 - 1.908)
Other	0.532** (0.301 - 0.940)	0.464* (0.215 - 1.001)	0.63 (0.268 - 1.481)				3.551 (0.687 - 18.348)	0.658 (0.305 - 1.422)	0.263** (0.094 - 0.741)	0.751 (0.194 - 2.907)	0.493** (0.276 - 0.881)
Married	0.969 (0.814 - 1.152)	0.871 (0.707 - 1.074)	1.145 (0.880 - 1.490)	0.908 (0.752 - 1.097)	1.615** (1.033 - 2.525)	0.72 (0.407 - 1.273)	1.912*** (1.195 - 3.059)	0.996 (0.750 - 1.323)	0.726** (0.556 - 0.948)	0.982 (0.663 - 1.456)	0.957 (0.784 - 1.167)
Smoker	0.822* (0.654 - 1.034)	1.032 (0.769 - 1.384)	0.697** (0.496 - 0.979)	0.866 (0.678 - 1.106)	0.727 (0.454 - 1.164)	1.182 (0.502 - 2.785)	0.488*** (0.306 - 0.777)	0.966 (0.717 - 1.302)	1.155 (0.776 - 1.718)	0.79 (0.491 - 1.272)	0.865 (0.678 - 1.104)
Constant	1.104 (0.816 - 1.494)	1.492** (1.063 - 2.093)	0.981 (0.654 - 1.471)	1.172 (0.824 - 1.667)	0.854 (0.460 - 1.584)	2.335** (1.038 - 5.252)	0.783 (0.464 - 1.323)	0.928 (0.645 - 1.337)	0.769 (0.536 - 1.103)	1.226 (0.657 - 2.290)	1.046 (0.739 - 1.482)

Note: Referent group = standard work schedule; Control variables include sex, education, race/ethnicity, occupational industry, marital status, smoking status.
*** p<0.01, ** p<0.05.

Table C.9. Fully controlled weighted multivariate logistic regression models examining the association between work hours at young adulthood (wave 4) and diabetes at early mid-life (wave 5), controlling for sociodemographic and health risk factors. Presented as odds ratios with 95% confidence intervals.

	Full Sample	Female	Male	White	Black	Hispanic	HS or Less	Some College	BA+	Service Industry	Other Industry
Nonstandard	1.276* (0.957 - 1.702)	1.445* (0.996 - 2.098)	1.027 (0.634 - 1.662)	1.32 (0.903 - 1.932)	1.142 (0.734 - 1.775)	1.438 (0.439 - 4.713)	1.519 (0.847 - 2.724)	1.167 (0.757 - 1.797)	1.141 (0.679 - 1.919)	1.244 (0.687 - 2.252)	1.201 (0.843 - 1.712)
Irregular	1.058 (0.682 - 1.643)	1.171 (0.690 - 1.987)	0.896 (0.446 - 1.798)	0.881 (0.533 - 1.457)	1.618 (0.708 - 3.699)	1.053 (0.173 - 6.405)	1.859 (0.616 - 5.612)	0.965 (0.527 - 1.768)	0.799 (0.404 - 1.580)	1.34 (0.545 - 3.294)	0.953 (0.547 - 1.661)
Female	1 (0.738 - 1.356)			1.018 (0.676 - 1.532)	0.946 (0.554 - 1.618)	0.78 (0.362 - 1.683)	1.47 (0.796 - 2.716)	1.234 (0.812 - 1.875)	0.565** (0.341 - 0.936)	0.793 (0.438 - 1.438)	1.066 (0.744 - 1.528)
Some College	0.508*** (0.352 - 0.734)	0.465*** (0.294 - 0.734)	0.497** (0.274 - 0.901)	0.569** (0.352 - 0.920)	0.515* (0.260 - 1.022)	0.344** (0.131 - 0.899)				0.538** (0.303 - 0.954)	0.493*** (0.295 - 0.824)
BA+	0.406*** (0.270 - 0.609)	0.279*** (0.168 - 0.464)	0.567* (0.292 - 1.101)	0.370*** (0.209 - 0.656)	0.633 (0.337 - 1.186)	0.315* (0.093 - 1.068)				0.578* (0.301 - 1.112)	0.372*** (0.215 - 0.643)
Black	3.660*** (2.711 - 4.942)	3.445*** (2.441 - 4.861)	4.130*** (2.401 - 7.104)				3.322*** (1.707 - 6.466)	2.713*** (1.679 - 4.384)	5.847*** (3.310 - 10.328)	4.485*** (2.540 - 7.920)	3.484*** (2.500 - 4.856)
Hispanic	1.782*** (1.204 - 2.636)	1.512 (0.859 - 2.663)	2.135*** (1.247 - 3.655)				2.274* (0.986 - 5.243)	1.352 (0.699 - 2.615)	1.853 (0.874 - 3.927)	1.573 (0.660 - 3.750)	1.916*** (1.235 - 2.974)
Other	1.199 (0.578 - 2.487)	2.514** (1.198 - 5.277)	0.377 (0.082 - 1.730)				1.714 (0.328 - 8.971)	1.434 (0.456 - 4.507)	0.858 (0.225 - 3.275)	1.443 (0.251 - 8.312)	1.154 (0.514 - 2.590)
Married	0.897 (0.664 - 1.213)	0.835 (0.599 - 1.162)	0.958 (0.572 - 1.606)	0.82 (0.547 - 1.230)	1.113 (0.616 - 2.012)	0.862 (0.378 - 1.967)	1.24 (0.633 - 2.429)	0.753 (0.485 - 1.169)	0.878 (0.486 - 1.585)	0.763 (0.415 - 1.402)	0.94 (0.656 - 1.346)
Smoker	0.767 (0.550 - 1.070)	0.96 (0.609 - 1.514)	0.592** (0.362 - 0.966)	0.78 (0.498 - 1.220)	0.738 (0.449 - 1.214)	0.988 (0.382 - 2.553)	0.71 (0.385 - 1.310)	0.87 (0.553 - 1.369)	0.706 (0.339 - 1.470)	0.665 (0.367 - 1.205)	0.79 (0.535 - 1.167)
Constant	0.197*** (0.131 - 0.295)	0.221*** (0.136 - 0.358)	0.193*** (0.105 - 0.357)	0.204*** (0.121 - 0.343)	0.594 (0.304 - 1.160)	0.47 (0.166 - 1.335)	0.129*** (0.065 - 0.255)	0.108*** (0.066 - 0.176)	0.102*** (0.045 - 0.230)	0.260*** (0.124 - 0.545)	0.186*** (0.112 - 0.308)

Note: Referent group = standard work schedule; Control variables include sex, education, race/ethnicity, occupational industry, marital status, smoking status.
*** p<0.01, ** p<0.05.

Table C.10. Fully controlled weighted multivariate logistic regression models examining the association between work hours at young adulthood (wave 4) and hypertension at early mid-life (wave 5), controlling for sociodemographic and health risk factors. Presented as odds ratios with 95% confidence intervals.

	Full Sample	**Female**	**Male**	**White**	**Black**	**Hispanic**	**HS or Less**	**Some College**	**BA+**	**Service Industry**	**Other Industry**
Nonstandard	1.052 (0.864 - 1.281)	1.204 (0.947 - 1.531)	0.863 (0.603 - 1.236)	1.052 (0.838 - 1.323)	1.425 (0.859 - 2.363)	1.032 (0.448 - 2.375)	0.935 (0.552 - 1.582)	1.193 (0.885 - 1.609)	0.915 (0.682 - 1.226)	1.013 (0.696 - 1.474)	1.084 (0.823 - 1.428)
Irregular	0.812 (0.602 - 1.096)	0.571*** (0.379 - 0.859)	1.302 (0.824 - 2.056)	0.799 (0.556 - 1.148)	1.306 (0.505 - 3.374)	0.638 (0.215 - 1.893)	0.521 (0.223 - 1.219)	0.833 (0.548 - 1.267)	0.862 (0.556 - 1.335)	0.602 (0.318 - 1.138)	0.914 (0.660 - 1.266)
Female	0.318*** (0.260 - 0.390)			0.286*** (0.223 - 0.365)	0.611* (0.362 - 1.029)	0.293*** (0.154 - 0.559)	0.381*** (0.229 - 0.631)	0.336*** (0.250 - 0.452)	0.277*** (0.204 - 0.377)	0.428*** (0.275 - 0.665)	0.293*** (0.232 - 0.371)
Some College	1.018 (0.789 - 1.313)	0.953 (0.691 - 1.315)	1.01 (0.645 - 1.581)	1.096 (0.820 - 1.465)	0.816 (0.425 - 1.564)	0.865 (0.357 - 2.098)				1.178 (0.684 - 2.030)	0.954 (0.706 - 1.288)
BA+	0.775 (0.595 - 1.008)	0.734 (0.526 - 1.026)	0.774 (0.502 - 1.196)	0.817 (0.608 - 1.097)	0.665 (0.308 - 1.436)	0.727 (0.329 - 1.609)				0.777 (0.438 - 1.380)	0.765* (0.565 - 1.035)
Black	1.866*** (1.457 - 2.391)	2.450*** (1.836 - 3.268)	1.241 (0.795 - 1.938)				2.002* (0.987 - 4.062)	1.720*** (1.160 - 2.552)	2.073*** (1.397 - 3.078)	2.317** (1.171 - 4.585)	1.775*** (1.339 - 2.353)
Hispanic	0.885 (0.636 - 1.232)	0.898 (0.578 - 1.394)	0.857 (0.525 - 1.398)				0.954 (0.472 - 1.929)	0.846 (0.513 - 1.392)	0.869 (0.548 - 1.377)	0.911 (0.410 - 2.026)	0.867 (0.606 - 1.241)
Other	0.459*** (0.299 - 0.704)	0.529** (0.292 - 0.957)	0.391** (0.189 - 0.806)				0.703 (0.140 - 3.521)	0.451* (0.197 - 1.030)	0.420** (0.210 - 0.838)	0.381 (0.101 - 1.431)	0.475*** (0.303 - 0.745)
Married	0.857 (0.706 - 1.041)	0.844 (0.685 - 1.040)	0.917 (0.649 - 1.298)	0.894 (0.717 - 1.115)	1.106 (0.689 - 1.776)	0.762 (0.335 - 1.731)	1.154 (0.707 - 1.883)	0.9 (0.679 - 1.192)	0.744* (0.551 - 1.003)	0.957 (0.599 - 1.528)	0.813* (0.649 - 1.019)
Smoker	1.229* (0.988 - 1.529)	1.569*** (1.191 - 2.069)	0.926 (0.658 - 1.304)	1.354** (1.052 - 1.743)	0.788 (0.407 - 1.526)	1.732 (0.700 - 4.284)	0.784 (0.509 - 1.207)	1.510** (1.075 - 2.121)	1.328 (0.799 - 2.206)	1.418 (0.861 - 2.335)	1.219 (0.948 - 1.566)
Constant	3.607*** (2.588 - 5.027)	1.118 (0.781 - 1.600)	3.982*** (2.429 - 6.530)	3.488*** (2.374 - 5.125)	4.778*** (2.023 - 11.287)	3.820*** (1.827 - 7.987)	3.697*** (2.154 - 6.345)	3.196*** (2.238 - 4.562)	3.355*** (2.293 - 4.910)	2.474*** (1.272 - 4.813)	4.060*** (2.851 - 5.782)

Note: Referent group = standard work schedule; Control variables include sex, education, race/ethnicity, occupational industry, marital status, smoking status.
*** p<0.01, ** p<0.05.

Table C.11. Fully controlled weighted multivariate logistic regression models examining the association between work hours at young adulthood (wave 4) and high inflammation at early mid-life (wave 5), controlling for sociodemographic and health risk factors. Presented as odds ratios with 95% confidence intervals.

	Full Sample	Female	Male	White	Black	Hispanic	HS or Less	Some College	BA+	Service Industry	Other Industry
Nonstandard	1.145 (0.946 - 1.386)	1.001 (0.770 - 1.301)	1.349* (0.968 - 1.879)	0.998 (0.783 - 1.271)	1.638** (1.067 - 2.512)	1.32 (0.566 - 3.078)	1.465* (0.934 - 2.300)	1.218 (0.902 - 1.646)	0.803 (0.531 - 1.213)	0.761 (0.506 - 1.144)	1.311** (1.034 - 1.663)
Irregular	1.001 (0.721 - 1.391)	0.941 (0.624 - 1.419)	1.079 (0.654 - 1.778)	1.027 (0.704 - 1.499)	0.981 (0.447 - 2.153)	0.717 (0.145 - 3.536)	0.991 (0.401 - 2.448)	1.304 (0.781 - 2.178)	0.775 (0.503 - 1.195)	1.08 (0.526 - 2.221)	0.929 (0.656 - 1.315)
Female	2.218*** (1.840 - 2.675)			2.271*** (1.778 - 2.901)	2.132*** (1.415 - 3.213)	2.025** (1.163 - 3.525)	2.820*** (1.781 - 4.466)	2.081*** (1.551 - 2.791)	2.082*** (1.562 - 2.774)	1.387 (0.913 - 2.105)	2.477*** (2.011 - 3.052)
Some College	0.853 (0.660 - 1.102)	0.692** (0.487 - 0.983)	1.051 (0.712 - 1.550)	0.883 (0.640 - 1.218)	0.79 (0.467 - 1.338)	0.853 (0.420 - 1.736)				0.597** (0.384 - 0.927)	0.944 (0.687 - 1.298)
BA+	0.558*** (0.411 - 0.759)	0.432*** (0.292 - 0.637)	0.723 (0.456 - 1.146)	0.527*** (0.360 - 0.772)	0.724 (0.398 - 1.316)	0.795 (0.348 - 1.814)				0.344*** (0.175 - 0.679)	0.616*** (0.438 - 0.865)
Black	1.547*** (1.232 - 1.943)	1.446*** (1.119 - 1.869)	1.596** (1.108 - 2.298)				1.787 (0.989 - 3.229)	1.323 (0.927 - 1.889)	1.849*** (1.185 - 2.884)	1.671* (0.936 - 2.983)	1.531*** (1.194 - 1.964)
Hispanic	1.03 (0.775 - 1.370)	0.951 (0.655 - 1.381)	1.149 (0.669 - 1.974)				0.946 (0.460 - 1.946)	0.853 (0.556 - 1.308)	1.365 (0.808 - 2.307)	1.919* (0.890 - 4.135)	0.931 (0.679 - 1.277)
Other	0.706 (0.414 - 1.205)	0.803 (0.436 - 1.479)	0.585 (0.250 - 1.367)				1.389 (0.352 - 5.481)	0.968 (0.444 - 2.110)	0.379* (0.120 - 1.194)	0.436 (0.131 - 1.455)	0.758 (0.434 - 1.326)
Married	0.868 (0.721 - 1.045)	0.831 (0.657 - 1.051)	0.907 (0.660 - 1.248)	0.916 (0.740 - 1.133)	0.991 (0.644 - 1.523)	0.528 (0.267 - 1.041)	1.369 (0.816 - 2.296)	0.796* (0.608 - 1.043)	0.780* (0.587 - 1.037)	0.858 (0.563 - 1.308)	0.879 (0.718 - 1.077)
Smoker	1.045 (0.813 - 1.342)	0.913 (0.684 - 1.218)	1.247 (0.838 - 1.856)	1.105 (0.836 - 1.461)	1.158 (0.681 - 1.968)	0.533 (0.230 - 1.236)	0.79 (0.487 - 1.280)	1.114 (0.799 - 1.553)	1.327 (0.822 - 2.144)	1.061 (0.672 - 1.677)	1.041 (0.802 - 1.351)
Constant	0.481*** (0.349 - 0.663)	1.452* (0.994 - 2.121)	0.349*** (0.217 - 0.563)	0.469*** (0.322 - 0.684)	0.595* (0.323 - 1.094)	0.665 (0.289 - 1.534)	0.353*** (0.202 - 0.617)	0.434*** (0.302 - 0.624)	0.307*** (0.216 - 0.436)	1.01 (0.534 - 1.909)	0.402*** (0.276 - 0.585)

Note: Referent group = standard work schedule; Control variables include sex, education, race/ethnicity, occupational industry, marital status, smoking status.
*** p<0.01, ** p<0.05.

Table C.12. Fully controlled weighted multivariate logistic regression models examining the association between work hours at young adulthood (wave 4) and high LDL-cholesterol at early mid-life (wave 5), controlling for sociodemographic and health risk factors. Presented as odds ratios with 95% confidence intervals.

	Full Sample	**Female**	**Male**	**White**	**Black**	**Hispanic**	**HS or Less**	**Some College**	**BA+**	**Service Industry**	**Other Industry**
Nonstandard	1.083 (0.810 - 1.449)	1.198 (0.787 - 1.826)	0.994 (0.672 - 1.469)	1.049 (0.721 - 1.526)	0.555 (0.261 - 1.181)	1.882 (0.813 - 4.356)	1.334 (0.660 - 2.695)	1.241 (0.797 - 1.932)	0.781 (0.474 - 1.288)	1.471 (0.800 - 2.704)	1.005 (0.711 - 1.421)
Irregular	0.854 (0.562 - 1.299)	1.011 (0.565 - 1.808)	0.743 (0.409 - 1.352)	0.749 (0.458 - 1.225)	1.241 (0.313 - 4.924)	0.59 (0.149 - 2.330)	1.468 (0.325 - 6.636)	1.459 (0.790 - 2.695)	0.457** (0.233 - 0.899)	1.827 (0.663 - 5.036)	0.666 (0.400 - 1.108)
Female	0.569*** (0.442 - 0.733)			0.526*** (0.392 - 0.706)	0.749 (0.367 - 1.529)	0.765 (0.308 - 1.899)	0.375*** (0.223 - 0.630)	0.657** (0.469 - 0.920)	0.530*** (0.369 - 0.761)	0.762 (0.415 - 1.400)	0.514*** (0.397 - 0.666)
Some College	1.264 (0.830 - 1.925)	1.786** (1.046 - 3.049)	1.043 (0.621 - 1.753)	1.097 (0.633 - 1.903)	2.225 (0.805 - 6.155)	1.081 (0.343 - 3.409)				1.656 (0.770 - 3.561)	1.134 (0.699 - 1.839)
BA+	1.153 (0.760 - 1.748)	1.647* (0.939 - 2.888)	0.974 (0.575 - 1.649)	1.113 (0.677 - 1.830)	1.649 (0.564 - 4.826)	0.893 (0.282 - 2.826)				0.935 (0.371 - 2.357)	1.138 (0.689 - 1.878)
Black	1.15 (0.798 - 1.657)	1.601* (0.993 - 2.581)	0.87 (0.498 - 1.520)				0.586 (0.212 - 1.623)	1.336 (0.804 - 2.222)	1.371 (0.844 - 2.226)	1.385 (0.556 - 3.445)	1.114 (0.752 - 1.649)
Hispanic	1.294 (0.800 - 2.091)	1.515 (0.858 - 2.676)	1.15 (0.546 - 2.423)				1.196 (0.405 - 3.531)	1.65 (0.907 - 3.002)	0.941 (0.429 - 2.060)	0.722 (0.212 - 2.464)	1.456 (0.875 - 2.423)
Other	1.227 (0.638 - 2.359)	0.903 (0.330 - 2.477)	1.52 (0.677 - 3.414)				0.454 (0.086 - 2.390)	2.615* (0.895 - 7.639)	0.794 (0.263 - 2.398)	0.933 (0.235 - 3.706)	1.3 (0.678 - 2.492)
Married	1.011 (0.774 - 1.320)	0.946 (0.652 - 1.371)	1.093 (0.744 - 1.605)	0.909 (0.683 - 1.212)	1.474 (0.781 - 2.780)	0.687 (0.320 - 1.474)	1.541 (0.777 - 3.056)	1.002 (0.679 - 1.480)	0.872 (0.561 - 1.355)	0.571* (0.319 - 1.024)	1.181 (0.874 - 1.597)
Smoker	1.05 (0.769 - 1.434)	1.202 (0.771 - 1.874)	0.979 (0.614 - 1.561)	1.165 (0.840 - 1.614)	0.438* (0.168 - 1.141)	1.953 (0.519 - 7.355)	0.748 (0.388 - 1.443)	1.528** (1.006 - 2.323)	0.711 (0.362 - 1.395)	1.05 (0.531 - 2.073)	1.006 (0.687 - 1.474)
Constant	0.304*** (0.193 - 0.480)	0.117*** (0.067 - 0.204)	0.369*** (0.215 - 0.635)	0.361*** (0.205 - 0.635)	0.256** (0.089 - 0.730)	0.384* (0.125 - 1.180)	0.330*** (0.166 - 0.658)	0.268*** (0.170 - 0.423)	0.475*** (0.295 - 0.764)	0.259*** (0.100 - 0.675)	0.315*** (0.188 - 0.528)

Note: Referent group = standard work schedule; Control variables include sex, education, race/ethnicity, occupational industry, marital status, smoking status.
*** $p<0.01$, ** $p<0.05$.

Table C.13. Weighted logistic regression of work schedules and alternative measures of diabetes and hypertension at young adulthood (wave 4) by gender, race/ethnicity, education, and occupational industry. Presented as odds ratios with 95% confidence intervals.

	Full Sample	Female	Male	White	Black	Hispanic	HS or Less	Some College	BA+	Service Industry	Other Industry
Diabetes											
Nonstandard	1.212 (0.774 - 1.899)	1.11 (0.571 - 2.156)	1.189 (0.640 - 2.211)	1.425 (0.720 - 2.821)	1.082 (0.468 - 2.501)	0.699 (0.191 - 2.557)	1.61 (0.843 - 3.074)	0.858 (0.456 - 1.616)	1.253 (0.437 - 3.593)	0.651 (0.259 - 1.636)	1.396 (0.744 - 2.621)
Irregular	1.181 (0.631 - 2.210)	1.049 (0.441 - 2.495)	1.2 (0.517 - 2.790)	1.064 (0.469 - 2.414)	0.825 (0.229 - 2.978)	1.684 (0.569 - 4.980)	0.714 (0.144 - 3.536)	1.878 (0.926 - 3.808)	0.293 (0.060 - 1.420)	0.424 (0.067 - 2.668)	1.472 (0.746 - 2.905)
Hypertension											
Nonstandard	0.846 (0.676 - 1.058)	0.934 (0.641 - 1.359)	0.804 (0.605 - 1.070)	0.822 (0.611 - 1.107)	1.148 (0.757 - 1.742)	0.728 (0.307 - 1.725)	0.795 (0.538 - 1.173)	0.917 (0.690 - 1.219)	0.697 (0.419 - 1.159)	0.829 (0.501 - 1.374)	0.862 (0.674 - 1.104)
Irregular	0.768 (0.550 - 1.072)	0.714 (0.378 - 1.350)	0.797 (0.534 - 1.189)	0.625** (0.406 - 0.962)	1.562 (0.858 - 2.843)	0.633 (0.151 - 2.643)	0.918 (0.443 - 1.904)	0.973 (0.594 - 1.595)	0.399*** (0.214 - 0.743)	0.492 (0.198 - 1.222)	0.843 (0.584 - 1.217)

Note: Referent group = standard work schedule; Control variables include sex, education, race/ethnicity, occupational industry, marital status, smoking status, supervisor role, number of worked hours per week, and length of employment.
*** p<0.01, ** p<0.05.

Table C.14. Weighted logistic regressions of work schedules at young adulthood (wave 4) and alternative measures of diabetes, hypertension, and high cholesterol at early mid-life (wave 5) by gender, race/ethnicity, education, and occupational industry. Presented as odds ratios with 95% confidence intervals.

	Full Sample	Female	Male	White	Black	Hispanic	HS or Less	Some College	BA+	Service Industry	Other Industry
Diabetes											
Nonstandard	1.341 (0.934 - 1.925)	1.515 (0.906 - 2.534)	1.051 (0.540 - 2.048)	1.646 (0.967 - 2.803)	0.819 (0.407 - 1.645)	1.06 (0.349 - 3.221)	2.080 (0.986 - 4.386)	1.177 (0.703 - 1.970)	0.841 (0.308 - 2.296)	1.463 (0.639 - 3.350)	1.256 (0.809 - 1.949)
Irregular	1.518 (0.800 - 2.880)	1.255 (0.520 - 3.028)	1.689 (0.699 - 4.079)	1.546 (0.717 - 3.330)	0.697 (0.205 - 2.366)	4.455 (0.773 - 25.686)	3.752** (1.066 - 13.203)	1.798 (0.781 - 4.140)	0.448 (0.161 - 1.247)	1.534 (0.424 - 5.553)	1.545 (0.733 - 3.253)
Hypertension											
Nonstandard	1.123 (0.870 - 1.450)	1.036 (0.676 - 1.588)	1.146 (0.809 - 1.623)	1.065 (0.773 - 1.467)	1.327 (0.762 - 2.310)	1.101 (0.458 - 2.648)	1.717** (1.033 - 2.855)	1.073 (0.717 - 1.606)	0.852 (0.524 - 1.387)	1.157 (0.658 - 2.035)	1.196 (0.881 - 1.624)
Irregular	1.185 (0.814 - 1.727)	0.838 (0.466 - 1.509)	1.427 (0.848 - 2.400)	1.126 (0.748 - 1.695)	0.832 (0.300 - 2.308)	2.002 (0.515 - 7.779)	1.674 (0.529 - 5.291)	1.779 (0.976 - 3.241)	0.627 (0.371 - 1.061)	1.134 (0.353 - 3.645)	1.277 (0.877 - 1.858)
High Cholesterol											
Nonstandard	1.034 (0.794 - 1.346)	0.98 (0.681 - 1.411)	1.054 (0.710 - 1.564)	0.983 (0.685 - 1.411)	1.159 (0.636 - 2.114)	1.011 (0.415 - 2.459)	1.723 (0.912 - 3.256)	0.947 (0.619 - 1.449)	0.8 (0.486 - 1.316)	0.957 (0.528 - 1.732)	1.139 (0.810 - 1.600)
Irregular	0.969 (0.670 - 1.401)	0.849 (0.472 - 1.528)	1.051 (0.625 - 1.767)	0.951 (0.604 - 1.498)	0.957 (0.334 - 2.743)	0.476 (0.072 - 3.137)	1.174 (0.366 - 3.761)	1.700 (0.952 - 3.034)	0.480** (0.257 - 0.899)	1.479 (0.523 - 4.180)	0.912 (0.608 - 1.368)

Note: Referent group = standard work schedule; Control variables include sex, education, race/ethnicity, occupational industry, marital status, smoking status.
*** p<0.01, ** p<0.05.

Table C.15. Weighted logistic regression of work schedules and alternative measure of obesity at young adulthood (wave 4) by gender, race/ethnicity, education, and occupational industry. Presented as odds ratios with 95% confidence intervals.

	Full Sample	Female	Male	White	Black	Hispanic	HS or Less	Some College	BA+	Service Industry	Other Industry
Nonstandard	0.944	0.908	0.943	0.961	0.977	0.987	1.035	0.958	0.733**	0.779	1.015
	(0.809 - 1.102)	(0.763 - 1.081)	(0.758 - 1.173)	(0.788 - 1.171)	(0.749 - 1.273)	(0.639 - 1.525)	(0.776 - 1.380)	(0.768 - 1.196)	(0.561 - 0.957)	(0.569 - 1.067)	(0.857 - 1.202)
Irregular	0.949	0.877	1.011	0.926	0.808	2.204**	0.977	0.800	1.056	0.85	0.977
	(0.796 - 1.131)	(0.672 - 1.146)	(0.786 - 1.302)	(0.755 - 1.137)	(0.482 - 1.356)	(1.109 - 4.383)	(0.591 - 1.617)	(0.615 - 1.040)	(0.794 - 1.404)	(0.538 - 1.344)	(0.801 - 1.191)
Female	0.683***			0.616***	1.333	0.741	1.176	0.687***	0.485***	0.832	0.648***
	(0.610 - 0.764)			(0.541 - 0.701)	(0.996 - 1.782)	(0.480 - 1.144)	(0.937 - 1.477)	(0.573 - 0.823)	(0.416 - 0.566)	(0.646 - 1.072)	(0.575 - 0.731)
Some College	0.967	0.701***	1.086	0.947	0.951	1.152				0.761*	1.027
	(0.823 - 1.137)	(0.550 - 0.894)	(0.905 - 1.303)	(0.769 - 1.165)	(0.626 - 1.447)	(0.728 - 1.822)				(0.563 - 1.027)	(0.853 - 1.237)
BA+	0.634***	0.419***	0.838	0.599***	0.932	0.599				0.464***	0.678***
	(0.532 - 0.756)	(0.331 - 0.530)	(0.666 - 1.054)	(0.479 - 0.749)	(0.640 - 1.357)	(0.358 - 1.002)				(0.316 - 0.682)	(0.548 - 0.840)
Black	1.677***	2.470***	1.132				1.223	1.503***	2.665***	1.484	1.705***
	(1.425 - 1.973)	(1.984 - 3.075)	(0.899 - 1.427)				(0.831 - 1.800)	(1.174 - 1.923)	(1.948 - 3.646)	(0.962 - 2.288)	(1.428 - 2.036)
Hispanic	1.569***	1.764***	1.382*				1.26	1.728***	1.468	1.233	1.652***
	(1.301 - 1.894)	(1.368 - 2.274)	(0.991 - 1.927)				(0.894 - 1.775)	(1.279 - 2.334)	(0.996 - 2.162)	(0.725 - 2.099)	(1.347 - 2.026)
Other	0.824	0.696	0.936				1.14	0.735	0.728	0.563**	0.879
	(0.591 - 1.148)	(0.436 - 1.109)	(0.638 - 1.373)				(0.514 - 2.527)	(0.435 - 1.243)	(0.529 - 1.001)	(0.326 - 0.971)	(0.619 - 1.250)
Married	1.262***	1.064	1.520***	1.216***	1.392**	1.348	1.393**	1.277***	1.172	1.03	1.299***
	(1.138 - 1.399)	(0.920 - 1.231)	(1.285 - 1.797)	(1.082 - 1.367)	(1.011 - 1.916)	(0.970 - 1.875)	(1.059 - 1.831)	(1.067 - 1.527)	(0.985 - 1.394)	(0.772 - 1.374)	(1.154 - 1.462)
Supervisor	0.997	0.994	0.995	0.995	0.991	0.842	0.985	0.899	1.135	1.310**	0.941
	(0.877 - 1.134)	(0.848 - 1.164)	(0.831 - 1.191)	(0.851 - 1.164)	(0.722 - 1.360)	(0.606 - 1.170)	(0.744 - 1.304)	(0.742 - 1.089)	(0.936 - 1.377)	(1.009 - 1.702)	(0.812 - 1.089)
Total Jobs	0.945	0.963	0.92	0.925	0.961	0.682	0.816	0.948	0.997	0.948	0.953
	(0.761 - 1.173)	(0.729 - 1.272)	(0.674 - 1.254)	(0.708 - 1.208)	(0.642 - 1.440)	(0.359 - 1.299)	(0.490 - 1.360)	(0.698 - 1.289)	(0.721 - 1.379)	(0.597 - 1.507)	(0.769 - 1.181)
Working Years	1.017	1.009	1.022	1.012	1.029	1.041	1.008	1.01	1.046***	1.03	1.013
	(0.996 - 1.038)	(0.985 - 1.034)	(0.993 - 1.052)	(0.989 - 1.035)	(0.970 - 1.091)	(0.971 - 1.115)	(0.969 - 1.049)	(0.983 - 1.038)	(1.013 - 1.080)	(0.981 - 1.081)	(0.992 - 1.035)
Smoker	0.647***	0.917	0.508***	0.634***	0.542***	0.75	0.540***	0.602***	1.069	0.635***	0.652***
	(0.553 - 0.757)	(0.721 - 1.167)	(0.420 - 0.614)	(0.531 - 0.756)	(0.373 - 0.787)	(0.399 - 1.410)	(0.415 - 0.703)	(0.486 - 0.745)	(0.744 - 1.538)	(0.451 - 0.893)	(0.556 - 0.765)
Constant	2.419***	2.278***	2.162***	2.749***	2.512***	3.009***	2.267***	2.604***	1.544**	2.579***	2.405***

	(1.930 - 3.031)	(1.709 - 3.037)	(1.660 - 2.815)	(2.107 - 3.587)	(1.636 - 3.857)	(1.654 - 5.474)	(1.582 - 3.250)	(2.069 - 3.277)	(1.110 - 2.149)	(1.621 - 4.102)	(1.859 - 3.112)

Note: Referent group = standard work schedule; Control variables include sex, education, race/ethnicity, occupational industry, marital status, smoking status, supervisor role, number of worked hours per week, and length of employment.
*** $p<0.01$, ** $p<0.05$.

Table C.16. Weighted logistic regressions of work schedules at young adulthood (wave 4) and alternative measure of obesity at early mid-life (wave 5) by gender, race/ethnicity, education, and occupational industry. Presented as odds ratios with 95% confidence intervals.

	Full Sample	Female	Male	White	Black	Hispanic	HS or Less	Some College	BA+	Service Industry	Other Industry
Nonstandard	1.04 (0.808 - 1.339)	1.098 (0.804 - 1.499)	0.933 (0.618 - 1.410)	0.998 (0.753 - 1.323)	0.994 (0.465 - 2.122)	1.495 (0.573 - 3.898)	0.845 (0.443 - 1.611)	1.138 (0.779 - 1.663)	0.962 (0.664 - 1.393)	0.731 (0.464 - 1.151)	1.173 (0.846 - 1.627)
Irregular	0.774 (0.544 - 1.102)	0.524*** (0.334 - 0.823)	1.326 (0.777 - 2.265)	0.726 (0.484 - 1.090)	0.68 (0.234 - 1.972)	1.639 (0.366 - 7.342)	1.144 (0.407 - 3.217)	0.733 (0.436 - 1.230)	0.7 (0.424 - 1.155)	0.435** (0.220 - 0.859)	0.884 (0.636 - 1.230)
Female	0.741*** (0.611 - 0.898)			0.647*** (0.520 - 0.804)	1.896** (1.030 - 3.492)	0.909 (0.458 - 1.801)	1.238 (0.727 - 2.109)	0.93 (0.678 - 1.276)	0.534*** (0.386 - 0.738)	0.707 (0.454 - 1.100)	0.762*** (0.621 - 0.935)
Some College	1.09 (0.788 - 1.507)	0.915 (0.584 - 1.436)	1.071 (0.676 - 1.696)	1.263 (0.866 - 1.842)	0.818 (0.392 - 1.709)	0.629 (0.185 - 2.142)				1 (0.577 - 1.734)	1.109 (0.773 - 1.590)
BA+	0.608*** (0.452 - 0.818)	0.456*** (0.295 - 0.704)	0.748 (0.488 - 1.147)	0.664** (0.467 - 0.944)	1.123 (0.558 - 2.261)	0.345* (0.116 - 1.027)				0.513** (0.296 - 0.888)	0.622*** (0.444 - 0.873)
Black	2.269*** (1.601 - 3.215)	3.536*** (2.253 - 5.548)	1.499* (0.951 - 2.365)				2.243** (1.148 - 4.381)	1.469 (0.883 - 2.445)	4.070*** (2.516 - 6.584)	2.144** (1.037 - 4.432)	2.279*** (1.591 - 3.265)
Hispanic	1.919*** (1.305 - 2.822)	2.123*** (1.306 - 3.451)	1.623 (0.903 - 2.914)				2.651* (0.871 - 8.070)	1.537 (0.812 - 2.910)	1.925** (1.004 - 3.689)	1.58 (0.573 - 4.360)	1.956*** (1.272 - 3.008)
Other	0.517** (0.308 - 0.866)	0.613* (0.349 - 1.077)	0.419** (0.180 - 0.973)				5.017* (0.796 - 31.626)	0.826 (0.368 - 1.853)	0.334*** (0.168 - 0.664)	0.956 (0.312 - 2.932)	0.472*** (0.271 - 0.822)
Married	0.985 (0.802 - 1.210)	0.9 (0.692 - 1.171)	1.153 (0.822 - 1.617)	1.015 (0.803 - 1.282)	1.576 (0.785 - 3.165)	0.352** (0.147 - 0.841)	1.663** (1.034 - 2.676)	0.953 (0.647 - 1.403)	0.886 (0.667 - 1.177)	0.915 (0.563 - 1.488)	0.998 (0.809 - 1.231)
Smoker	0.813 (0.630 - 1.048)	1.199 (0.859 - 1.674)	0.577*** (0.398 - 0.835)	0.919 (0.688 - 1.227)	0.892 (0.510 - 1.560)	0.285*** (0.122 - 0.664)	0.471*** (0.284 - 0.781)	0.841 (0.591 - 1.197)	1.358 (0.824 - 2.239)	1.056 (0.627 - 1.778)	0.755* (0.563 - 1.013)
Constant	4.178*** (2.909 - 6.001)	3.692*** (2.240 - 6.086)	4.044*** (2.424 - 6.747)	3.981*** (2.677 - 5.918)	4.551*** (1.941 - 10.673)	23.332*** (4.735 - 114.978)	3.588*** (2.023 - 6.362)	4.161*** (2.665 - 6.495)	3.179*** (2.081 - 4.855)	5.337*** (2.678 - 10.637)	3.967*** (2.654 - 5.930)

Note: Referent group = standard work schedule; Control variables include sex, education, race/ethnicity, occupational industry, marital status, smoking status.
*** $p<0.01$, ** $p<0.05$.

Table C.17. Weighted logistic regressions of work schedules at young adulthood and CVH outcomes early mid-life (wave 5) by gender, race/ethnicity, education, and occupational industry and controlling for CVH outcomes at wave 4. Presented as odds ratios with 95% confidence intervals.

	Full Sample	Female	Male	White	Black	Hispanic	HS or Less	Some College	BA+	Service Industry	Other Industry
Obesity[1]											
Nonstandard	1.305**	1.657***	1.03	1.107	2.529***	1.433	0.937	1.485**	1.242	1.217	1.401**
	(1.048 - 1.624)	(1.242 - 2.209)	(0.692 - 1.534)	(0.855 - 1.432)	(1.472 - 4.345)	(0.611 - 3.360)	(0.562 - 1.563)	(1.037 - 2.125)	(0.813 - 1.898)	(0.759 - 1.949)	(1.046 - 1.876)
Irregular	1.031	0.781	1.381	1.054	1.223	0.724	0.536	1.236	1.004	1.019	1.067
	(0.724 - 1.469)	(0.489 - 1.248)	(0.806 - 2.365)	(0.683 - 1.627)	(0.514 - 2.914)	(0.236 - 2.225)	(0.168 - 1.708)	(0.661 - 2.310)	(0.595 - 1.695)	(0.330 - 3.149)	(0.733 - 1.553)
Diabetes[2]											
Nonstandard	1.375	1.468	1.169	1.438	1.314	1.349	1.52	1.216	1.37	1.51	1.229
	(1.000 - 1.890)	(0.981 - 2.199)	(0.679 - 2.013)	(0.967 - 2.138)	(0.782 - 2.210)	(0.281 - 6.486)	(0.818 - 2.824)	(0.753 - 1.964)	(0.747 - 2.511)	(0.772 - 2.953)	(0.818 - 1.845)
Irregular	1.212	1.363	0.995	1.186	1.607	0.849	2.497	1.259	0.722	1.789	1.078
	(0.769 - 1.911)	(0.782 - 2.376)	(0.492 - 2.010)	(0.705 - 1.993)	(0.672 - 3.844)	(0.164 - 4.396)	(0.838 - 7.443)	(0.663 - 2.391)	(0.361 - 1.444)	(0.635 - 5.038)	(0.639 - 1.820)
Hypertension[3]											
Nonstandard	1.126	1.345**	0.866	1.156	1.484	1.013	0.936	1.302	1.003	1.058	1.163
	(0.913 - 1.389)	(1.061 - 1.705)	(0.596 - 1.259)	(0.908 - 1.471)	(0.850 - 2.592)	(0.445 - 2.304)	(0.544 - 1.612)	(0.949 - 1.788)	(0.726 - 1.388)	(0.713 - 1.571)	(0.877 - 1.540)
Irregular	0.821	0.605**	1.202	0.874	1.016	0.494	0.515	0.749	0.959	0.634	0.915
	(0.598 - 1.128)	(0.395 - 0.926)	(0.749 - 1.931)	(0.598 - 1.278)	(0.344 - 3.000)	(0.160 - 1.524)	(0.231 - 1.151)	(0.464 - 1.208)	(0.603 - 1.525)	(0.344 - 1.170)	(0.632 - 1.324)
High Inflammation[4]											
Nonstandard	1.167	0.996	1.440	1.02	1.758**	1.336	1.338	1.380	0.758	0.791	1.326**
	(0.928 - 1.467)	(0.767 - 1.295)	(0.977 - 2.120)	(0.767 - 1.358)	(1.054 - 2.932)	(0.507 - 3.514)	(0.813 - 2.204)	(0.981 - 1.940)	(0.438 - 1.312)	(0.481 - 1.301)	(1.020 - 1.723)
Irregular	0.957	0.933	0.966	1.021	0.761	0.649	0.926	1.275	0.736	0.911	0.902
	(0.669 - 1.370)	(0.642 - 1.357)	(0.504 - 1.855)	(0.678 - 1.536)	(0.329 - 1.763)	(0.112 - 3.777)	(0.344 - 2.490)	(0.761 - 2.136)	(0.468 - 1.158)	(0.485 - 1.710)	(0.602 - 1.351)

Note: Control variables include sex, education, race/ethnicity, occupational industry, marital status, smoking status and wave 4 obesity[1], wave 4 diabetes[2], wave 4 hypertension[3], wave 4 high inflammation[4]
*** p<0.01, ** p<0.05.

PROJECT CONCLUSION

This dissertation sought to understand whether state labor preemption laws were impacting mental health and health care access outcomes for workers across the US, and whether irregular and nonstandard scheduling practices were shaping poor cardiovascular health outcomes for workers in young adulthood and early mid-life. I began by examining whether variations in and dimensions of four US state labor preemption laws were associated with adverse mental health outcomes (Paper 1) and cost related barriers to health care for workers (Paper 2) across gender, income, race/ethnicity, education, and insurance coverage strata using nationally representative BRFSS data merged with state preemption law measures. Additionally, I examined whether nonstandard or irregular work schedules, a potential outcome of preempted fair scheduling laws, were getting 'under the skin' of workers at young adulthood and early mid-life using biomarkers of cardiovascular health from Add Health, a nationally representative longitudinal survey, and whether risk factors for cardiovascular disease were patterned by gender, race/ethnicity, education, or employment in the service industry (Paper 3).

Synthesis of Findings

Recent research suggests state preemption laws are associated with negative population health outcomes (Wolf, Monnat & Montez, 2021; Melton-Fant, 2020; Montez, 2018) and may pose a significant threat to public health (Carr et al., 2020; Pomeranz & Pertschuk, 2017; Institute of Medicine, 2011). In light of this evolving empirical and conceptual evidence, I hypothesized that variations in and dimensions of four state preempted labor laws would be associated with worse mental health outcomes (Paper 1) and cost-related barriers to health care (Paper 2) for workers across the US. I suspected these outcomes would be exacerbated for females, workers of color, and individuals with less education given evidence that these groups are disproportionately employed in precarious jobs (Blair et al., 2019). Moreover, I anticipated that state preemption laws that protected temporal aspects of work (i.e. work schedules and hours) would have a greater impact on the odds of reporting adverse mental health and health care access outcomes in light of Schneider and Harknett's (2019) recent study that found temporal dimensions of work were a stronger predictor of workers' health than economic aspects of work (i.e. wages) (Papers 1 and 2). For Paper 3, I anticipated that workers with nonstandard and irregular work hours would be at increased odds of poor cardiovascular health, and these outcomes would once again be particularly pronounced for female workers, workers of color, and less educated workers over time given evidence of the many poor health outcomes associated with nonstandard and irregular working hours (e.g., Books et al., 2020; Ramin et al., 2014). I also anticipated that workers employed in service and retail jobs would be a greater risk for poor cardiovascular health as compared to their non-service sector working counterparts based on evidence that service and retail workers are disproportionately subjected to precarious working conditions and may be more likely to experience health consequences as a result (Appelbaum et al. 2003; Enchautegui, Johnson, & Gelatt, 2015; Golden, 2001). While all three papers offer important insights about different aspects of the association between state preemption and worker's mental health, health care and cardiovascular health, findings across studies were mixed and did not fully support these hypotheses.

Main Findings of Paper 1

Using 2019 data from the Behavioral Risk Factor Surveillance System (BRFSS) Survey (Centers for Disease Control and Prevention, 2019) merged with state-level preemption law measures (Economic Policy Institute, 2019), I employed a series of weighted bivariate and multivariate logistic regression models to examine whether the number of state labor preemption laws or the type of state preemption laws enacted were associated with adverse mental health outcomes. Findings showed that female workers that lived in states that enacted multiple preemptive labor laws were at significantly higher odds of reporting poor mental health as compared with female workers who lived in states with no preemption, and this was pronounced for Hispanic females. When considering whether the effects of economic or temporal dimensions of state labor preemption exacerbated poor mental health, I found state preemption of temporal-based preemption laws such as fair scheduling ordinances significantly increased the likelihood of poor mental health for female workers, and low income and Hispanic females in particular. Notably, I found no statistically significant associations between any amount or type of state preemption and poor mental health for male workers, suggesting that the mental health consequences of state preemption disproportionately impact females.

Main Findings of Paper 2

I also used 2019 data from the Behavioral Risk Factor Surveillance System (BRFSS) Survey (Centers for Disease Control and Prevention, 2019) merged with state-level preemption law measures (Economic Policy Institute, 2019) to examine whether the number of state preemption laws, or the type of state preemption laws enacted were associated with cost-related barriers to health care for US workers with a high school education or less. The weighted logistic regression models were stratified by worker's gender, race/ethnicity, and health coverage. Findings suggest female workers with a high school education or less that lived in states with multiple preempted labor laws were at significantly higher odds of reporting cost-related barriers to health care regardless of health coverage, and this association was pronounced for Black and white female workers. Female workers with no health coverage that lived in states with both economic and temporal labor preemption laws were at increased odds of experiencing cost-related barriers to health care suggesting that both protected time and health coverage may be important factors for worker's health. Notably, Black male workers were at significantly higher odds of experiencing barriers to health care in states with multiple preemption laws supporting evidence that racial inequities in health may be exacerbated by state preemption.

Main Findings of Paper 3

To examine whether nonstandard or irregular work schedules were associated with poor CVH outcomes, I used wave 2008-2009 (wave 4) and 2016-2018 (wave 5) biomarker data from Add Health. Findings indicated that nonstandard work schedules were associated with some poor cardiovascular health outcomes for particular groups of workers over time. For instance, female workers, Black workers, and workers employed outside of the service sector with nonstandard work schedules during young adulthood were at greater risk of obesity in mid-life. Additionally, Black workers and non-service sector workers with nonstandard schedules in young adulthood were at increased risk of high inflammation at early mid-life. There was little evidence of an association between irregular work schedules and poor CVH outcomes for workers at young adulthood and early mid-life with exception of Black workers with irregular work schedules who were found to be at increased odds of hypertension in young adulthood.

Implications

Findings from this research have a number of implications for social justice, labor policy, and health equity. First, by utilizing an equity-first lens this dissertation expands on current calls to understand whether the effects of state preemption laws have the potential to advance or hinder public health and health equity (Carr et al., 2020). By specifically interrogating whether various instances and forms of four state labor preemption laws protect or exacerbate different indicators of population health, this dissertation offers new evidence about important associations between different aspects of commonly preempted labor laws and workers' mental health, health care access, and cardiovascular health.

Second, this work provides several important insights into how preemption may disproportionately shape health inequities by place and across populations. For instance, findings suggest that the number of state preemptive actions enacted, and the type of preemptive laws passed have heterogenous rather than uniform health effects for different subgroups of workers. As a result, policy makers should consider different types of policies and practices to address population health inequities across the US, both at state and local levels.

Additionally, this research responds to recent calls to investigate whether state governments may have used their legislative authority to exacerbate health inequities through state preemption efforts (Carr et al., 2020), and offers new insights about the ways in which policy structures and institutional actors can create and perpetuate discriminatory policies and systems that worsen health inequities. Moreover, this research highlights the importance of considering the role of upstream factors (or fundamental causes) in producing health inequities instead of merely the downstream presence or absence of risk factors for health.

Finally, this work provides important health considerations for policymaking across sectors and advances a health in all policies (HiAP) agenda for promoting equity. By focusing on a specific policy area and not a single public health issue, this work moves beyond the scope of traditional public health research to consider a multitude of factors with specific attention to state policy contexts and how they have potentially positive or negative impacts on the health and well-being of communities, as well as the distribution of those impacts across populations.

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