Title

State-level minimum wages as a poverty intervention for reducing child and family health disparities: examining impacts on food insecurity and child maltreatment mortality

Author

Neumann, Krista

Publication Date

2024

Peer reviewed|Thesis/dissertation

State-level minimum wages as a poverty intervention for reducing child and family health disparities: examining impacts on food insecurity and child maltreatment mortality

By

Krista Neumann

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Epidemiology

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Corinne Riddell, Co-Chair
Professor Barbara Laraia, Co-Chair
Professor Hilary Hoynes

Spring 2024

Abstract

State-level minimum wages as a poverty intervention for reducing child and family health disparities: examining impacts on food insecurity and child maltreatment mortality

by

Krista Neumann

Doctor of Philosophy in Epidemiology

University of California, Berkeley

Professor Corinne Riddell, Co-Chair
Professor Barbara Laraia, Co-Chair

Numerous adverse health outcomes in the United States (U.S.) are closely linked with poverty and low income, affecting children from birth through adulthood and influencing not only their health, but also their quality of life and later economic opportunities. Further, structural factors including discriminatory policies, systems, and societal norms perpetuate income inequality, hinder upward economic mobility, and ultimately exacerbate long-standing health inequities by race and ethnicity. Therefore, addressing the root causes of poverty through structural interventions is crucial for reducing disease burden, mortality rates, and health disparities.

Minimum wage policies have been proposed as one potential upstream solution for alleviating poverty. Minimum wage laws address poverty by setting a baseline income level for workers so that they are better able to meet their basic cost-of-living needs. Since low income is an important risk factor for both food insecurity and child maltreatment, it is possible that increased minimum wages could enhance family health and nutrition and prevent maltreatment-related deaths. However, little is currently known about how effective minimum wages are at addressing these outcomes. Further, existing research to date has not adequately examined whether minimum wages mitigate or exacerbate related disparities. This dissertation aims to augment the existing body of literature and fill a critical gap by examining the impact of minimum wages on food insecurity prevalence and child maltreatment mortality rates. We also aim to identify whether these impacts vary among traditionally marginalized subpopulations (i.e. those defined by race and ethnicity, educational attainment, etc.) and thus explore how minimum wages effect existing disparities in food insecurity and child maltreatment. In all studies, we utilize large U.S. population-representative datasets and leverage the changing dollar amounts of state-level minimum wages over time.

The first chapter provides additional background and context on minimum wages and motivates their potential as a structural solution to poverty. It summarizes the current

research investigating the effects of minimum wages on poverty and health outcomes, including food insecurity and child maltreatment. It also informs our focus on examining heterogenous effects by race and ethnicity, educational attainment, and family structure.

Chapters 2 and 3 examine the relationship between state-level minimum wages and household food insecurity using data from the largest population-based survey assessing food insecurity in the U.S. Chapter 2 employs a cross-sectional design to estimate the effect of $1 increase in minimum wage on the food insecurity prevalence of 624,770 working-aged households between 2002 and 2019. This work reveals no overall population-level effect of minimum wages on food insecurity while uncovering heterogeneous effects across demographic groups. Specifically increases in minimum wages are found to help protect against food insecurity for households whose head had less than a high school diploma, households headed by single women, Indigenous households, and multiracial households (with children). In contrast, increases in minimum wage are found to increase food insecurity prevalence among Black and multiracial households (overall). Chapter 3 extends this work to look at the relationship between minimum wages and food insecurity among a subset of 15,845 households receiving government food (SNAP) benefits who disproportionally experience high levels of food insecurity as a whole. This population is especially important to examine given that public assistance benefits are mediated by income which makes the net effects of small changes in income difficult to predict. We find that the impact of state-level minimum wages on food insecurity among SNAP recipients depends on household characteristics such as age (elderly vs working aged), family structure (including presence of children and marital status of parents), race and ethnicity, and educational attainment. In both chapters 2 and 3 we discuss potential complex interactions with other safety-net programs which could be responsible for these heterogeneous effects.

Chapter 4 evaluates the impact of state-level minimum wages on child maltreatment-related mortality. We use death certificate data and a novel child maltreatment identification strategy to identify 24,025 deaths in children under 5 years of age between 2000 and 2019. We find that a $1 increase in minimum wage is not associated with child maltreatment-related deaths, but that stratified results suggest possible heterogeneity by racial-ethnic identity.

The final chapter provides a summary of all three studies and discusses how future research can build upon our results to better protect vulnerable populations and eliminate health disparities.

This work is dedicated to Hudson and the little peanut we can't wait to meet in a few months. I hope the world you grow up in is kinder, fairer, and provides more equal opportunities for all children to live healthy and fulfilling lives.

Table of Contents

List of figures

List of tables

Acknowledgements

"Many times a day I realise how much my own outer and inner life is built upon the labours of my fellow [humans], both living and dead, and how earnestly I must exert myself in order to give in return as much as I have received."

- Attributed to Albert Einstein

Like most, I would not be where I am today without the help, guidance, and support of many others. To my advisor and mentor Dr. Corinne Riddell, thank you for taking a chance on me. You have a remarkable ability to always guide me along the right path and illuminate the viable options while still allowing me to maintain ownership and decision-making power over my research. Your willingness to share your expertise and approaches to similar problems has been invaluable. I have learned so much from your thoughtful and critical feedback and you have helped me to become a better researcher, methodologist, and manuscript writer. On a personal note, I am incredibly grateful for the time you have invested into helping me navigate the challenges of graduate school (beginning in the middle of global pandemic no less!) and a career in academia. I look forward to future collaborations and partnerships.

To my dissertation committee members, Drs. Barbara Laraia and Hilary Hoynes, I am extraordinarily grateful for the constructive feedback, resources, and support you have provided to help me finish this dissertation on time. Dr. Laraia, your perspective is always refreshing, and you have been extremely helpful for contextualizing the findings presented in this dissertation. Your ability to point out important missed nuances never fails to surprise me. Dr. Hoynes, I could not have successfully completed an analysis of minimum wages without your economic expertise and guidance! I am honored you agreed to mentor me, and appreciative of the methodological and contextual insights you shared (and for your patience in navigating the interdisciplinary differences between economics and epidemiology). Your course on the economics of the Social Safety Net has been one of the most influential of my graduate career and I will undoubtably be applying my learnings to many future projects.

I would be remiss if I didn't also acknowledge the support and expertise of other faculty members, mentors, and research collaborators who shaped my trajectory and helped me to become a more thoughtful researcher, teacher, and colleague. Dr. Sandi McCoy – you have taught me everything I know about designing, facilitating, and teaching a successful epidemiology breath course. Your ability to create a space where GSIs feel both empowered to develop their pedagogical skills through creative license over their sections, but also supported through challenging situations via your expert guidance is something I hope to embody in my own academic career. I am delighted to have worked alongside you multiple times throughout my tenure. Dr. Jennifer Ahern, I am truly lucky to have had the opportunity to work so closely with you in multiple capacities: I have learned so much from your mentorship as a research collaborator, as well as from your teachings as both a student of your thought-provoking social epi class and as a GSI of your methods course. Your kindness and support throughout my PhD program are much appreciated. Dr. Patrick Bradshaw, I could not claim to be an epidemiologist without your expert methodological training. I am constantly referring to your lecture slides and readings to refresh my understanding of all things biostatistical. Dr. Susan Mason, thank you for introducing me to the nuances and challenges of child maltreatment epidemiology. Your deep expertise, fresh ideas, and thoughtful feedback has inspired me to continue down this line of research. Drs. Jeanie Santaularia and Kriszta Farkas, your friendship, collaboration, and advice have kept me sane throughout graduate school. Our conversations always teach me so much and leave me feeling fulfilled and inspired.

Throughout my time at Berkeley, I have been bolstered by the support and encouragement of my fellow students and classmates. I am especially grateful to Lila Sheira, Hilary Colbeth, Helena Archer, Julia Acker, and Mahader Tamene – you were the best QE study group I could have asked for; beyond untangling methodological nuances and providing valuable advice and insights, your comradery got me through graduate school (at the very least, I can say we had fun together!). To Emily Altman, Solis Winters, and Margae Knox, I am forever grateful for your ongoing friendship and support.

Most importantly, to my mom (Karen), dad (Ken) and sister (Kayla): your constant love, encouragement and belief in my abilities shaped me into the person I am today. I would not have been so bold, confident, or capable of pursuing a PhD if it hadn't been for you. And of course, I owe the biggest debt of gratitude to my husband, whose unwavering encouragement and ambition is why I decided to come back to graduate school in the first place. Richman, I cannot thank you enough for always providing me with the much needed emotional and tactical support at the times I most need it. Your steadfast love and commonsense advice have buoyed me when I've doubted myself. I cannot wait to see what the future holds for our little family.

I would also like to acknowledge that a version of Chapter 4 of this dissertation has been submitted for publication, under the title *U.S. state minimum wages and rates of maltreatment-related death among children*. Thank you to my coauthors – Stephanie Veazie, Dr. Susan Mason, Dr. Jennifer Ahern, and Dr. Corinne Riddell – for your valuable contributions to this paper and for allowing its inclusion in this dissertation. A special thank you to Dr. Patricia Schnitzer for your guidance on the use of maltreatment-related ICD codes utilized in this chapter.

Chapter 1: Introduction

1.1 Poverty and health in the U.S.

In the U.S., there is a well-established connection between income inequality and health disparities. From birth into adulthood, socio-economic status is a predictor of adverse health outcomes and lower quality of life. Socio-economic disadvantage has been linked to higher risks of preterm birth, low birthweight, and growth restriction.[1] Compared to children whose families have higher incomes, lower-income children experience higher rates of asthma, heart conditions, hearing problems, digestive disorders, and poorer self-reported health,[2] as well as lower academic achievement and higher rates of school drop-out.[3,4] The health effects of childhood poverty accumulate over time and compound with other environmental stressors and adverse childhood experiences – such as substandard housing, food insecurity, household dysfunction, neglect, and exposure to violence – leading to chronic stress, maladaptive coping and self-regulatory strategies, and ultimately poorer adult health.[5,6] Compared to wealthier Americans, low-income adults in the US have higher rates of heart disease, diabetes, stroke, and other chronic disorders,[7] and even lower life expectancies. In fact, recent research has documented a 10-to-15-year gap in life expectancy when comparing the most affluent 1 percent of individuals to the poorest 1 percent, suggesting that the longevity cost of being poor is equivalent to a lifetime of smoking.[8]

Not only is poverty detrimental to health, but it is also persistent and intergenerational. One in every ten children is persistently poor, which means they spend at least half of their childhood living below the federal poverty threshold.[4] Children who grow up living in poverty are more likely to become adults living in poverty, the probability of which is correlated with the length of time they spent in poverty as a child.[9] Further, intergenerational cycles of poverty are hard to break: there is only a 7.5% probability that a child born in the bottom fifth of the income distribution will reach the top fifth income distribution in adulthood.[10]

Factors such as race and ethnicity, educational attainment, and gender further interact with and compound the income-health dynamic. Prevalent and persistent poverty- and health-related disparities are more common among some racial-ethnic groups compared to others due to historical and ongoing structural factors (i.e. policies, practices, and societal patterns which perpetuate discriminatory beliefs through systems of housing, education, employment, health care, and criminal justice). For example: poverty rates are consistently highest among American Indian and Alaskan Natives, Black, and Hispanic households, disproportionate to their relative share of the total population;[11,12] similarly, Black children are less likely than White children to experience intergenerational economic mobility.[10] Importantly, research suggests that racial-ethnic identity and socioeconomic status have both separate and additive effects on a wide range of health status, health behavior, health care use, and health screening outcomes.[13,14] Similarly, higher educational attainment and higher income are both separately linked to better health outcomes.[15] Report of adverse childhood experiences – many of which are correlated with poverty – is associated with higher risk of unemployment later in life, and this relationship is mediated by educational attainment and marital status, especially among women.[16]

Taken together, identifying upstream, structural solutions to poverty that can help reduce persistent health disparities is an important public health priority.

1.2 Evidence on minimum wage, poverty, and health

Over the past few decades, minimum wage has been the subject of intense debates and policy evolution in the U.S., both at the federal and state level. The primary goal of setting a minimum wage is to establish a baseline income level for workers so that they can meet basic needs and contribute to economic growth through increased consumer spending.

Minimum wages may also be an important tool for systematically reducing poverty and long-standing inequities. Minimum wage workers are disproportionately more likely to be Hispanic or Black, have lower educational attainment, and be parents between the ages of 25 and 50.[17] It is hypothesized that one reason the U.S. has not experienced a significant reduction in poverty rates, despite overall improvements to living conditions, is because of stagnant wages and increasing inequality.[18] In fact, the federal minimum wage has only increased 3 times under the Fair Labor Standards Act since 2000 – rising from $5.15 to $7.25 per hour by 2009 where it has remained ever since[19] – though states and other localities are also able to set their own minimum wages. When a state, county or city's minimum wage is higher than the federal minimum wage, most employees are entitled to the highest minimum wage. Indeed, as of March 2024, 31 states (including the District of Columbia) and 61 counties and cities have set minimum wages higher than the federal minimum wage.[20,21] This variation in policy across geography and over time provides a salient opportunity for investigating the effects of minimum wages.

A vast literature examining the impacts of minimum wages generally supports the assertion that increases in minimum wage have little effect on overall employment while significantly increasing the earnings of low paid workers.[22–24] However, the evidence on the effects of minimum wages on health outcomes and behaviors is mixed, with many studies showing no impact.[25] Documented positive effects of minimum wage include improved self-reported overall and mental health of adult and teen workers, reduced work absenteeism, declines in non-drug suicides, fewer adolescent births, increased time spent with children, and fewer reports of child maltreatment and neglect, while documented negative effects of minimum wage include higher rates of obesity and BMI, health declines among workers without a college degree, lower math and reading test scores among low income children, and an increased prevalence of smoking.[25] This research also highlights disparities in effects: for example the benefits of increased minimum wages on self-reported health are concentrated among white women, with no impact found among Hispanic women, and while mothers experience more time with children when minimum wages rise, fathers do not see the same benefit.[25]

Many minimum wage studies are however limited by a narrow focus on a subgroup of workers (e.g. teenage workers) or in their choice of an appropriate control group to represent the counterfactual scenario (i.e. comparing across high vs low wage regions and/or demographic groups may introduce confounding factors).[22] Further still, many studies rely on difference-in-difference approaches to evaluate the impact of minimum wage policy changes. This technique has recently come under scrutiny due to biases in the two-way fixed effects estimator under certain scenarios.[26–30] (see Appendix B for details), which may call some estimates of effect into question.

This dissertation aims to build on the existing body of literature and fill a critical gap by utilizing U.S. population-representative datasets and leveraging the changing dollar amounts of state-level minimum wages over time to examine the (within-state) impact of minimum wages on child and family health outcomes. Specifically, chapters 2 and 3 assess effects on food insecurity prevalence while chapter 4 examines effects on child maltreatment-related death rates. In chapter 3, we restrict the population to those receiving Supplemental Nutrition Assistance Program (SNAP) benefits, a population with a high prevalence of food insecurity whose programmatic benefits change depending on household income. In all chapters we pay special attention to existing disparities and heterogeneity in effect among traditionally marginalized groups (i.e. those defined by race and ethnicity, educational attainment, etc.).

1.3 Food insecurity, poverty, and minimum wage

Approximately 170 million U.S. households were food insecure at some point during 2022, making food insecurity one of the nation's leading health and nutrition issues.[31] Households are considered food insecure if they are uncertain of having, or unable to acquire, at some time during the year, enough food to meet the needs of all their members because they had insufficient money or other resources for food.[31] Food insecurity is linked to a number of adverse and chronic health conditions in both children and adults, and for children, it can even effect development and educational performance.[32]

The strongest determinant of food insecurity is insufficient income.[33,34] Like with poverty, there are also stark disparities in food insecurity rates by race and ethnicity, with Black and Hispanic households consistently experiencing the highest levels of food insecurity compared to other racial-ethnic groups.[31] Higher rates of food insecurity have also been found among households with lower educational attainment, households with children – especially those headed by single parents – and those with incomes less than 185 percent of the federal poverty threshold.[33] SNAP is the largest food and nutrition program in the U.S., and aims to help fill some of this need. Households with income less than 130 percent of the federal poverty threshold are typically eligible and provided with money earmarked for the purchase of food. Research has shown that SNAP helps to reduce food insecurity and improve the health and well-being of many families.[35–44] At the same time, there is evidence that SNAP benefits are not sufficient to cover the food need gap,[45–49] and almost half of all households who received SNAP benefits in 2019 remained food-insecure.[50] Therefore, additional upstream interventions to increase household income, or the ability to purchase sufficient food, are warranted. Given the strong link between household income and food insecurity, raising the minimum wage has the potential to help mitigate food insecurity, and address related disparities.

In Chapter 2 of this dissertation, we aim to inform structural efforts to reduce food insecurity disparities by evaluating whether increases in state-level minimum wages reduce food insecurity prevalence overall and within important subgroups defined by race-ethnicity, educational attainment, family structure, and income relative to the federal poverty threshold. We utilize data from the Current Population Survey (the largest national survey assessing U.S. food insecurity each year) between 2002 and 2019 and estimate the effect of a $1 increase in state-level minimum wage on food insecurity prevalence among households with at least one working aged adult under 65 years of age via a linear probability model with state and year fixed effects and robust controls for hypothesized confounders. We also examine separate effects among households with children.

Since SNAP benefits are determined primarily based on household income, increases in minimum wage will lead to a reduction in SNAP benefits, and so it is not clear whether increased income will outweigh, net out, or be outweighed by the corresponding reduction in government assistance. In Chapter 3, we therefore aim to identify the effect of state-level minimum wages on food insecurity among SNAP recipients specifically. We further restrict the Current Population Survey to those who receive SNAP benefits and create a longitudinal dataset by linking households across two survey-years. We again use a linear probability model with state and year fixed effects, and control for several hypothesized confounders. We explore whether the effect varies by household demographics such as race and ethnicity, educational attainment, and family structure, and look separately at effects among elderly households (aged 65 or older) and working aged households (between ages 18 and 64) with and without children.

1.4 Child maltreatment, poverty, and minimum wage

The number of child deaths due to abuse and neglect – collectively referred to as child maltreatment – has been increasing in the U.S., from an estimated 460 reported maltreatment deaths in children under 19 years old in 2000 to 1,512 in 2019.[51] This statistic is likely an undercount, due to challenges in measuring maltreatment-related deaths. The National Child Abuse and Neglect Data System (NCANDS) aggregates information from individual state Child Protective Services (CPS) programs and welfare agencies and is commonly used as the source of information for children maltreatment incidence and mortality. However, it also has some well-known limitations. First, fluctuations in annual state-level CPS funding make it challenging to compare trends over place and time, since it is difficult to disentangle funding-related systems-level changes with true changes in underlying maltreatment. Second, it relies on child abuse and neglect reported to state child welfare agencies, which means that unreported maltreatment is not fully accounted.[52] This also means that some populations are overrepresented in the system compared to true maltreatment rates – namely those with lower incomes who interact more frequently with mandated reporters to maintain government benefits, and those historically marginalized who have been disproportionately scrutinized and surveilled – exacerbating disparities in reported maltreatment-related outcomes.[53–57]

Poverty is a well-established social determinant for child maltreatment, with consistent and robust evidence demonstrating a link between both household- and area-level poverty and child maltreatment rates.[58–60] Thus, policy-level interventions that increase household income, such as increases to the minimum wage, may provide parents with additional financial, mental and emotional resources needed for healthy parental functioning and lead to lower rates of child maltreatment. Studies have in fact demonstrated that increased income – and higher minimum wages – can lead to decreased reports of child abuse and neglect,[61–65] however we are not aware of any study examining the relationship been minimum wages and child maltreatment mortality.

Thus, in Chapter 4, we aim to evaluate the effectiveness of minimum wages as an upstream, structural-level poverty intervention for reducing child maltreatment mortality. To overcome reporting and funding biases associated with NCANDS data, we use death certificate data and an innovative approach to identify a set of child maltreatment-related deaths. We then calculate state-year-age death rates using aggregated death counts and population denominators. We utilize a linear regression with state and year fixed effects and robust standard errors to estimate incidence rate differences of the effect of a $1 increase in effective minimum wage on child maltreatment-related death rates, with appropriate confounder adjustment. Finally, we examine heterogeneity in effect by race and ethnicity using stratified models.

Chapter 2: Impacts of state-level minimum wages on food insecurity prevalence and heterogeneity by race-ethnicity, family structure, educational attainment, and income

2.1 Introduction

In 2022, 12.8% of all U.S. households, including over 6.4 million families with children, experienced food insecurity – the inability to reliably obtain nutritionally adequate and safe foods in socially acceptable ways – at some point during the year.[33] Food insecurity is not only common, but often detrimental to both mental and physical health, as well as the growth and development of children. Food-insecure adults are at a higher risk for some of the most common and chronic health conditions, such as diabetes, obesity, and hypertension.[32] Among children, food insecurity is linked to lower health status, more frequent colds, developmental risk, depression, anxiety and poor educational performance.[32] Additionally, these health conditions can be costly to both individuals and society, with food insecure individuals more likely to visit an emergency department compared to those who are food secure.[66] In fact, food insecurity is associated with excess healthcare expenditures of $77.5 billion annually,[67] and spending on national food assistance programs reached a record high of $83.3 billion in 2021.[68]

The strongest determinant of food insecurity is insufficient income,[33,34] which is shaped by factors at all levels of the socio-ecological environment (Figure 2.1): at the household level, income is affected by individual educational opportunities, skills and abilities, extended family supports and household/family relationships; at the institutional/organizational level, income is related to industry of employment, the presence of worker protections (such as unions), benefit packages (including paid leave and overtime pay), job security, and full- vs part-time work; at the community level, income may be determined by employment opportunities, availability of training programs, rurality, and other labor market forces; and at the systems level, income may be impacted by laws and policies, including local, state and federal minimum wage policies, availability and accessibility of safety-net programs, and other social determinants such as structural racism and gender discrimination which affect job entry and advancement. Increasing the minimum wage may therefore be an effective upstream intervention for raising income, and thus ability to afford food.

However, it is also possible that increased minimum wages could result in adverse conditions for some low-wage employees. While there is substantial evidence that minimum wage increases have minimal impact on employment levels and provide increases in earnings for low-wage workers overall,[22–24] research also indicates that there may be negative side-effects among some workers. Specifically, employment decreases in response to wage increases have been documented for tradeable sector jobs (i.e. occupations that produce goods or services for international trade such as manufacturing, agricultural, IT services, etc.).[24] Further, for families with income levels near the poverty line, up to 40% of increased income due to higher wages may be offset by a reduction in safety-net benefits.[23] More generally, increased minimum wages can also result in higher prices of goods and services if employers pass the costs of increased wages onto the consumer – a side effect which disproportionately impacts those with the lowest incomes.[69,70] Qualitative work among low-wage workers provides additional evidence to these downsides: many low-wage workers report experiencing reductions in public benefits or corresponding cost-of-living increases which offset their income gains due to increased wages.[71,72] Hence, it is unclear whether higher wages are enough to offset these potential negative consequences when it comes to food insecurity outcomes, especially for those who are already marginalized and at an increased underlying risk of food insecurity.

Research examining the impacts of U.S. minimum wages on food insecurity is limited. While the field of economics is quite rich with studies examining the impact of minimum wage policies on important economic indicators, including a growing literature exploring the effects on poverty, there are only a handful of studies which examine food insecurity as a specific outcome.[73–76] Previous research has found no overall effect of increased minimum wages on population-level food insecurity,[73–76] and one estimated harmful effects for workers under 30 years old with less than a high school degree.[73] Two of these studies examined minimum wage increases in only a single city,[74,76] while the other two, which both predate the most recent federally-mandated minimum wage increases between 2007 and 2009, were limited by imprecise estimates due to survey data which did not include food security information for all study years of interest.[73,75] Thus, further research using population-based samples is warranted to understand the impacts of minimum wage on food insecurity.

Additionally, while poverty is a key factor determining a household's food security, status,[33,34] food insecurity is distinct from poverty and not all low-income households are food insecure. In 2019, just over one third of households with incomes below the official poverty line were food insecure.[77] Food insecurity disproportionately affects low-income and minoritized communities, with rates varying by race and ethnicity, family structure, and educational attainment. The 2022 national food insecurity rate of 12.8% masks much higher rates among non-Hispanic Black- and Hispanic-headed households (22.4% and 20.8% respectively).[33] Households with children have a higher rate of food insecurity (17.3%) compared to those without children (11.0%), and households headed by single women experience more food insecurity than those headed by single men, though both have higher than average rates (33.1% vs. 21.2%, respectively).[33] In 43% of all food-insecure households, the most educated adult household member had a high school level education or less.[31] Given that race and ethnicity, family structure, and educational attainment are important household risk factors for insecurity,[34,50,78,79] and previous research found negative impacts of increased wages on young adults, there could be also be important heterogeneity in effect worth investigation.

In this study, we aimed to evaluate whether increases in state-level minimum wages reduced food insecurity prevalence overall and within important subgroups. This work may help inform structural efforts to reduce food insecurity disparities.

2.2 Data and Methods

2.2.1 Sample

With an average monthly sample size of 60,000 households,[80] the U.S. Current Population Survey is the largest national survey assessing U.S. food insecurity each year. It samples civilian, noninstitutional households via a multistage probability-based design. Households are interviewed over the course of sixteen months on a 4-8-4 rotation schedule whereby they participate for four consecutive months, take an eight-month hiatus, and then participate for another four consecutive months before exiting the sample. Households may enter the interview rotation during any calendar month, though only households whose four participation months include December are assessed for food insecurity. The Current Population Survey is designed to be population representative at both the national and state levels and is used to generate official estimates of food insecurity prevalence.

We used the Integrated Public Use Microdata Series[81] to gather data on households who participated in the Current Population Survey between 2002 and 2019 during the month of December (961,366 households). These dates were chosen to avoid confounding by time period: prior to 2002 food security questions were asked within different months and subject to seasonality biases (beginning in 2002 food security questions were consistently asked in December only), and the 2020 COVID-19 Pandemic markedly altered food security trends.[82] We restricted the sample to households with at least one working-aged adult between the ages of 18 and 64 years old who answered the food security module (625,333 households). We excluded those living in group quarters (563 households who resided in college dormitories, military barracks, group homes, missions, or shelters) since they were sampled as individuals and were not linked to other family members or household information.

2.2.2 Outcome: food security

During the December supplement of the Current Population Survey, one adult per sampled household is administered the U.S. Household Food Security Survey Module, which includes 18 items for households with children under the age of 18 years, and 10 items for households without children (Appendix A). Responses to this survey are used to categorize households as having high, marginal, low, or very low food security. Our main and subpopulation analyses used a binary food security classification, where households with high food security status were considered food secure while remaining households were considered food insecure. This definition of food insecurity differs from the official U.S. Department of Agriculture (USDA) definition which classifies households experiencing marginal food security as food secure.[83] Current research suggests that the experience of those with marginal food security more closely resembles the experience of food insecure households rather than that of food secure households, [84] and descriptive plots showing food security status trends over time support this assertion (Figure 2.2). We thus chose the broader definition of food insecurity for our main analyses and examined alternate classifications in sensitivity analyses.

2.2.3 Exposure: state minimum wage

We used data from the University of Kentucky Center for Poverty Research[85] to determine both the federal- and state-specific minimum wage in each year. We confirmed dates of any change in minimum wage via state government websites and used a weighted average of the pre- and post-change amounts as the minimum wage for that state-year. We defined effective minimum wage for each state-year to be the higher of the state or federal minimum wage since the majority of employees are entitled to such under The Fair Labor Standards Act.[86] Finally, we converted the nominal minimum wage to real 2019 dollars using the consumer price index[87] to account for inflation and changes in purchasing power over the study timeframe.

2.2.4 Statistical Analysis

First, we calculated unweighted descriptives on the study population and effective minimum wage changes over time. For these statistics, we considered states which either (i) had no state-level minimum wage, (ii) set their state minimum wage to follow the federal standard, or (iii) set their minimum wage below the federal floor (effectively allowing the federal minimum wage to take effect) to be “lower minimum wage” states, while all remaining states, whose minimum wage exceeded the federal standard at some point during the study period, were classified as “higher minimum wage” states.

Leveraging differences in the dollar amount of effective state minimum wages, we used a linear probability model[88,89] to estimate the effect of a $1 increase in real minimum wage on food insecurity prevalence among households with at least one working aged adult under 65 years of age. State fixed effects were included to eliminate confounding by unmeasured factors that varied across states, while year fixed effects were included to control for shared secular trends. We calculated 95% confidence intervals (95%CI) using robust standard errors clustered at the state level, and household food security supplement weights were included to account for participant selection factors and non-response. We included five nested models with increasing adjustment sets (see covariate descriptions below): (1) unadjusted; (2) model 1 plus adjustment for state and year fixed effects; (3) model 2 plus state-year confounders; (4) model 3 plus co-occurring policies; and (5) model 4 plus household-level demographics (Equation 2.1). We also calculated separate effects among households with children (who had at least one working aged adult under 64 years of age).

$$y_{ist} = \beta_0 + \beta_1 * MW_{st} + \beta_2 * \mathbf{S}_s + \beta_3 * \mathbf{Y}_t + \beta_4 * \mathbf{X}_{st} + \beta_5 * \mathbf{P}_{st} + \beta_6 * \mathbf{H}_{ist} + \varepsilon_{ist} \quad \text{(Eq. 2.1)}$$

Where: y_{ist} is a binary variable denoting whether or not household i in state s in year t is food insecure (y = 1 indicates food insecure): β_0 is the intercept; MW_{st} is the effective minimum wage for state s in year t with β_1 denoting the policy effect of interest; $\mathbf{S}_s$ is a vector of indicator variables for each state s with β_2 indicating each state fixed effect; $\mathbf{Y}_t$ is a vector of indicator variables for each year t with β_3 indicating each year fixed effect; $\mathbf{X}_{st}$ is a vector of the state- and time-varying confounders (figure 2.3) with β_4 representing the coefficients on these confounders; $\mathbf{P}_{st}$ is a vector of the state-year co-occurring policies (figure 2.3) with β_5 representing the coefficients on these policies; $\mathbf{H}_{ist}$ is a vector of the household-level demographics determining food insecurity status (figure 2.3) with β_6 representing the coefficients on these factors; and ε_{ist} is residual household-level variation.

2.2.5 Covariates

2.2.5.1 State-year confounders

We created a directed acyclic graph (Figure 2.3) to illustrate the hypothesized confounders that occur at the state-year level. Because research shows that increases in unemployment lead to increases in food insecurity at the state-level,[90–93] and we hypothesized that it may be an important economic indicator of population-level wellbeing used by policy makers when determining minimum wage laws, we adjusted for state-specific unemployment rates to reduce confounding.[85] Further, we considered housing costs as a proxy for cost-of-living, since housing is a major fixed expense impacting a household's ability to afford food.[91,94] Specifically, we included estimates of the median rent for a two bedroom apartment averaged across all counties in a state-year from the U.S. Department of Housing and Urban Development.[95] Median rent was converted to real 2019 dollars using the consumer price index.[87] To ensure these state-year confounders preceded minimum wage changes, both were lagged one year.

2.2.5.2 Co-occurring policies

Various safety net policies are administered at the state level each year, and their accessibility and generosity are important factors determining a family's food security status (Figure 2.3). To better isolate the effect of minimum wage policies, we adjusted for several co-occurring policies. First, we considered food assistance via the Supplemental Nutrition Assistance Program (SNAP), the National School Lunch Program (hereafter "School Lunch") and the National School Breakfast Program (hereafter "School Breakfast"). We described state-wide SNAP participation via state-year specific programmatic take-up rates[96] and characterized the availability and accessibility of school meal program using the ratio of state-year School Breakfast participation (the number of school children participating in the School Breakfast program)[85] to state-year School Lunch participation (the number of school children participating in the School Lunch program).[85] School Lunch participation is often used as a benchmark for participation in School Breakfast, given that School Lunch is more widely and consistently available across states.[93] We also included the following policies: Medicaid generosity scores (an index of program generosity derived from data on state-specific eligibility rules, administrative burdens, and benefits),[97] welfare generosity as measured by the Temporary Assistance for Needy Families 2-person benefit amount[85], and unemployment insurance generosity[98] calculated as the maximum available benefit dollar amount times the maximum available number of weeks. Both the welfare and unemployment insurance generosity variables were converted to real 2019 dollars using the consumer price index.[87]

2.2.5.3 Household-level determinants of food insecurity

A number of household-level factors are associated with a family's food security status including: race and ethnicity, educational attainment, family structure, living in a metropolitan area, and income (Figure 2.3).[34,50,78,79] To improve statistical efficiency, we included the head of household's race and ethnicity (Non-Hispanic American Indian/Alaska Native; Non-Hispanic Asian, Non-Hispanic Black; Non-Hispanic Hawaiian/Pacific Islander; Hispanic; Multiracial; Non-Hispanic White), educational attainment (less than high school; high school diploma or equivalent; some college; associate's, occupational or bachelor's degree; advanced degree), and marital status (married; separated or divorced; single male; single female), as well as the household's rurality (lives in a central city; lives outside a central city; does not live in a metropolitan area; unknown). All variables were available on the household record of the Current Population Survey. Note that because family income is impacted by wages, we did not adjust for family income.

2.2.6 Subpopulation Analyses

Given that we do not expect minimum wages to impact all households equally, we were interested in examining modification in effect among marginalized and vulnerable subgroups defined by race and ethnicity, family structure (i.e., single parents), educational attainment, and poverty. Since previous research has found negative impacts among young adults less than 30 years old, we also wanted to examine whether effects were different among this population specifically. We thus performed the following stratified analyses, using the same five aforementioned adjustment sets:

a) *Head of household race/ethnicity* (Non-Hispanic Asian; Non-Hispanic Black; Hispanic; Non-Hispanic Indigenous; Multiracial/Multiethnic; Non-Hispanic White). Due to small sample sizes, those who identified as Non-Hispanic American Indian/Alaska Natives and Non-Hispanic Hawaiian/Pacific Islanders were combined into the Non-Hispanic Indigenous category.

b) *Family structure*, as defined by the head of household's marital status, gender, and number of own children in household (No children; married with children; separated or divorced with children; male single parent; female single parent).

c) *Head of household educational attainment* (less than high school; high school diploma or equivalent; some college; college degree). Due to sample size, we collapsed those with a college degree at any level into a single category.

d) *Family's income to poverty ratio* calculated as the ratio of the household's total (actual) family income divided by the official poverty threshold used by the Census Bureau to evaluate poverty status. Official poverty thresholds are calculated based on income levels adjusted annually for inflation and vary according to household size and composition. Thus the income to poverty ratio provides a relative indicator of economic well-being while taking into consideration variations in family composition Note that this subpopulation analysis was performed on just over a quarter (27.1%) of the main study sample since detailed income and poverty cutoff information was only available for participants who entered the survey rotation in December and who thus also completed the Current Population Survey's Annual Social and Economic Supplement (ASEC) in March (see Supplemental Material for further details on the ASEC and how the supplements were linked). Income to poverty ratios were categorized as follows: below poverty cutoff (<100% of poverty threshold); 100-129% of poverty cutoff; 130-184% of poverty cutoff; and greater than 185% of poverty cutoff. These cut points were used since they represent typical income cutoffs for most safety-net programs (for example, those with income less than the official poverty cutoff are typically eligible for welfare, those with income below 130% of the poverty cutoff are typically eligible for SNAP and free school meals, and those with income less than 185% of the poverty cutoff are typically eligible for reduced price school meals and the Special Supplemental Nutrition Program for Women, Infants, and Children).

e) *Young vs more experienced workers*, defined by head of household's age (18-29 years old; 30-64 years old).

2.2.7 Sensitivity Analyses

We completed several sensitivity analyses to determine robustness to model assumptions. First, while the working age restriction was meant to ensure that the study sample was plausibly exposed to minimum wages, we also ran models on the full sample (and full sample with children) which did not restrict the population to households where at least one adult was less than 65 years of age. Considering that less than 5% of low-wage workers in the U.S. are over the age of 65, we expected that including those aged 65 years and older may slightly attenuate the results.

Second, while survey weights were used in all main and subpopulation models to correct for participant non-response and selection factors,[99,100] the use of survey weights for estimating inferential statistics is contested.[101] We thus performed unweighted analyses to determine if point estimates were materially altered. Weighted analyses most often result in increased instability and larger standard errors compared to unweighted analyses.[102]

Third, we examined an alternate specification of food insecurity. While we had good reason to consider those with marginal food security status as food insecure, we assessed whether results from our main model differed if food security was defined according to the official USDA definition, with those experiencing marginal food security classified as being food secure. We expected that treating those with marginal food security as being food secure could underestimate true food insecurity and thus result in increased minimum wages being less protective than they may be when those with marginal food security are classified as being food insecure.

Fourth, since it is more common in economics to present estimates adjusted for household-level factors before estimates adjusted for other confounders, we present an alternative order of adjustment sets: (a) unadjusted; (b) model a plus adjustment for state and year fixed effects; (c) model b plus household-level demographics; (d) model c plus state-year confounders; (e) model d plus co-occurring policies (i.e. the fully adjusted model). We did not expect fully adjusted estimates or confidence intervals to be impacted.

Fifth, to address the potential bias that may be induced in two-way fixed effects models (See Appendix B for discussion),[26–30] we explored an alternative hybrid fixed effects model with state-specific random intercepts (equation 2.2). This model included state-specific minimum wage means to control for fixed differences between states that may be correlated with minimum wages and thus control for between-cluster confounding.[103] It also included year-specific minimum wage means to control for differences between years that may be correlated with the exposure. This sensitivity analysis did not permit survey weights or clustered standard errors, so we compared it to the unweighted main model. We used the same adjustment sets as the main fixed effects analysis, replacing state and year fixed effects with state and year effective minimum wage means, but omit the unadjusted model from comparison. If results are robust to model form, we would expect that conclusions from the hybrid fixed effects model would not be materially different compared to conclusions from our (unweighted) main model.

$$y_{ist} = \beta_{00} + \beta_{0s} + \beta_1 {*} MW_{st} + \beta_2 {*} \overline{MW}_s + \beta_3 {*} \overline{MW}_t + \beta_4 {*} \boldsymbol{X}_{st} + \beta_5 {*} \boldsymbol{P}_{st} + \beta_6 {*} \boldsymbol{H}_{ist} + \varepsilon_{ist} \quad \text{(Eq.2. 2)}$$

Where: y_{ist} is a binary variable denoting whether or not household i in state s in year t is food insecure (y = 1 indicates food insecure): β_{00} is the intercept representing the grand mean; β_{0s} is the random effects state-specific intercept; MW_{st} is the effective minimum wage for state s in year t with β_1 denoting the policy effect of interest; $\overline{MW}_s$ is the average minimum wage for state s across all years with β_2 indicating the coefficient on this term; $\overline{MW}_t$ is the average minimum wage for year t across all states with β_3 indicating the coefficient on this term; $\boldsymbol{X}_{st}$ is a vector of the state- and time-varying confounders (figure 2.3) with β_4 representing the coefficients on these confounders; $\boldsymbol{P}_{st}$ is a vector of the state-year co-occurring policies (figure 2.3) with β_5 representing the coefficients on these policies; $\boldsymbol{H}_{ist}$ is a vector of the household-level demographics determining food insecurity status (figure 2.3) with β_6 representing the coefficients on these factors; and ε_{ist} is residual household-level variation.

Finally, we were interested in examining what level of food security is affected by the change in minimum wage, and by how much. We therefore used separate linear probability models to estimate the effect of a $1 increase in minimum wage comparing food insecurity prevalence differences between: (i) Marginal food security and high food security, (ii) Low food security and high food security, and (iii) Very low food security and high security.

All analyses were performed using R version 4.1.3 (2022-03-10). This study was not considered human subjects research and no human subjects approval was required.

2.3 Results

2.3.1 Descriptive statistics

Between 2002 and 2019, effective minimum wages rose by an average of $1.16 (SD: $1.30) across all states (Supplemental Figure 2.1). Sixteen states were "lower minimum wage" states who either had no state-level minimum wage, set their state minimum wage to follow the federal standard, or set their minimum wage below the federal floor, effectively allowing the federal minimum wage to take effect. The largest effective minimum wage increases were $4.89 in D.C. and $3.78 in Colorado and New York, while twenty-one states experienced a decrease of $0.07 (Supplemental Figure 2.2).

The study sample was comprised of 624,770 households who had at least one working aged adult between the ages of 18 and 64 years old, and their characteristics are detailed in Table 2.1. Almost a quarter (22.4%) of households experienced food insecurity at some point during the study and about 28% of the sample lived in lower minimum wage states. About 1 in 6 (15.5%) households were headed by a young worker between the ages of 18 and 29. Family structure was similar across lower and higher minimum wage states, though higher minimum wage states tended to be slightly more educated (64.2% of household heads having more schooling than a high school diploma, compared to 59.7% in lower wage states). Racial and ethnic diversity also varied. Higher minimum wage states had a higher proportion of Asian head of households (hereafter, "households", for brevity): 4.3% in higher minimum wage states compared to 1.9% in lower minimum wage states. Lower minimum wage states had a greater proportion of Black households: 14.2% in lower minimum wage states compared to 8.6% in higher minimum wage states. About 1 in 10 of all households (10.3%) were living below the federal poverty line, with lower minimum wage states having a greater proportion of low-income households (26.4% of households in lower minimum wage states had income less than 185% of the poverty cutoff, compared to 22.6% in higher minimum wage states).

2.3.2 Results from main model analysis

In our main analysis, we found no overall effect of minimum wages on food insecurity prevalence. (Figure 2.4, Supplemental Table 2.1). Unadjusted Model 1 found that a $1 increase in minimum wage was associated with an estimated reduction in household food insecurity prevalence of 36 per 10,000 households [Prevalence difference (PD): -36, 95%CI: (-49, -22)]. Accounting for unobserved state differences and secular trends (Model 2) attenuated the result towards the null, reducing prevalence estimates to a decrease of 15 per 10,000 households [PD: -15, 95%CI: (-29, -1)]. The addition of state-year confounders and co-occurring policies in Models 3 and 4 and household demographics in Model 5 further reduced the magnitude of the estimated effect of minimum wages on the prevalence of food insecurity to be practically null [PD: 2, 95%CI: (-9, 12)]. Prevalence difference estimates and interpretations among households with children were very similar for our preferred model 5, though the confidence intervals were wider.

2.3.3 Results from subpopulation analyses

Stratified analyses of the fully adjusted Model 5 by subpopulations of interest revealed important heterogeneity in the estimated impact of minimum wages on food insecurity prevalence (Figure 2.5, Supplemental Table 2.2). We considered effect sizes whose magnitude was 50 per 10,000 households or more (0.5%) to be a meaningful change in food insecurity prevalence. Given that we ran 42 fully adjusted stratified subgroup models (including the models that stratify by households with children), we would expect around two of these models to have statistically significant results at the 5% level, due to chance alone. However, we found statistically significant effects of minimum wage on food insecurity prevalence among 18 subgroups.

Fully adjusted model 5 estimated that a $1 increase in minimum wage decreased the prevalence of food insecurity among Indigenous households, both with and without children, between 249 and 402 per 10,000 households [PD for all households: -249, 95%CI: (-370, -127); PD for households with children: -402, 95%CI: (-550, -254)]. Increases in minimum wages did not meaningfully impact food insecurity among Asian households [PD for all households: 14, 95%CI: (0, 28); PD for households with children: -16, 95%CI: -40, 8)], Hispanic households [PD for all households: -14, 95%CI: (-47, 19); PD for households with children: -11, 95%CI: (-49, 28)] or White households [PD for all households: 2, 95%CI: (-5, 8); PD for households with children: 26, 95%CI: (16, 36)]. However, increases in minimum wages increased food insecurity prevalence for Black households by an estimated 83 to 94 per 10,000 households [PD for all households: 94, 95%CI: (56, 132); PD for households with children: 83, 95%CI: (13, 153)]. The impact of minimum wages for Multiracial households depended on whether they had children: A $1 increase in minimum wage led to an estimated increase in food insecurity prevalence of 142 per 10,000 households overall [PD: 142, 95%CI: (39, 245)], but an estimated decrease in food insecurity prevalence of 134 per 10,000 households with children [PD: -134, 95%CI: (-237, -32)].

Increases in minimum wages were helpful for households headed by single parent females, decreasing food insecurity prevalence by an estimated 80 per 10,000 households [PD: -80, 95%CI: (-132, -28)]. Remaining household structures were not meaningfully impacted by changes in minimum wage.

Among households whose head had less than a high school diploma, increases in minimum wage led to a food insecurity prevalence decrease of an estimated 89 to 92 per 10,000 households [PD for all households: -92, 95%CI: (-135, -48); PD for households with children: -89, 95%CI: (-133, -45)]. Those with higher levels of educational attainment were not meaningfully impacted by changes in minimum wage.

Results stratified by a family's income to poverty ratio revealed a gradient of effect estimates for those below 185% of the poverty cutoff: among all households, there was no effect of minimum wages on food insecurity for those living below the poverty cutoff [PD: 0, 95%CI: (-76, 76)], while those between 100-184% of the poverty cutoff experienced increased food security prevalence between 101 and 130 per 10,000 households when minimum wages increased [PD among those between 100-129% of poverty cutoff: 101, 95%CI: (25, 178); PD among those between 130-184% of poverty cutoff: 130, 95%CI: (62, 198)]. Similarly, for households with children, a $1 increase in minimum wage led to a decrease in food insecurity prevalence among those living below the poverty cutoff [PD: -110, 95%CI: (-203, -17)], no change in food security for those between 100-129% of the poverty cutoff [PD: 26, 95%CI: (-71, 123)], and an increase in food security among those between 130-184% of the poverty cutoff [PD: 117, 95%CI: (4, 230)]. Households living above 185% of the poverty cutoff were not meaningfully affected by changes in minimum wage.

When examining younger vs more experienced workers, we found that minimum wages did not impact food insecurity for workers of any age, regardless of presence of children.

2.3.4 Results from sensitivity analyses

Results were not materially altered when we removed the working age restriction to include the elderly population (Supplemental Figure 2.3), nor when we ran unweighted analyses (Supplemental Figure 2.4). Survey-weighted analyses were more precise than unweighted analyses (See Appendix C for discussion). Treating those with marginal food security as being food secure did not change effect estimates but did result in more precise confidence intervals (Supplemental Figure 2.5). As expected, reordering the adjustment sets did not impact point estimates or confidence intervals for fully adjusted models (Supplemental Figure 2.6). Similarly, point estimates from the (unweighted) hybrid models were similar to unweighted fixed effect model estimates, though confidence intervals were smaller (Supplemental Figure 2.7).

While we did find slight heterogeneity in effect among those with different levels of food insecurity, these differences were minor, with point estimates less than 13 per 10,000 households in magnitude for the fully adjusted Model 5, and not meaningful (Supplemental Figure 2.8).

2.4 Discussion

Similar to previous research,[73–76] this study found no population-level effect of increased minimum wages on overall food insecurity prevalence among working aged households and working aged households with children.

Stratified estimates by race and ethnicity, family structure, educational attainment, and income-to-poverty ratio, however, illustrated heterogeneity in effect. Specifically, we found meaningful protective effects of increased minimum wages on food insecurity among historically marginalized subgroups that would be expected to benefit most from higher minimum wages: households headed by an individual with less than a high school education[a], households with children living below the poverty line, and households headed by single women. These results are consistent with research documenting larger impacts of minimum wage increases among those with a high school education or less, women, and both Black and Hispanic workers.[24] While we also estimated protective effects among historically marginalized indigenous households (with and without children) and multiracial households (with children only), Black households and multiracial households overall were estimated to have experienced an increase in food insecurity when minimum wages rose. Past research has found that higher minimum wages may lead to job loss among restaurant workers,[104] and those working in tradeable sectors (e.g. manufacturing, agricultural, IT services).[24] If Black and multiracial individuals (without children) make up a disproportionate share of the workforces that are negatively impacted by minimum wage increases, it is plausible that these groups were more likely to be impacted by such negative consequences. Similarly, increased income could lead to decreased safety-net support as means-tested programmatic benefits typically decrease when income increases. The racialized administrative burdens for U.S. safety net programs are well documented.[105,106] For example Black applicants applying for welfare and other public assistance are more likely to report experiencing discrimination based on their race.[107] These administrative burdens, combined with the fact that Black children are more likely than White children to receive food benefits,[108] could support the idea that increased minimum wages may lead to a loss or reduction of benefits for a higher proportion of Black families that is not offset by the additional income, resulting in increased food insecurity. These hypotheses warrant further investigation.

Unlike characteristics such as race and ethnicity, education, family structure, and age, increases in minimum wage may alter a family's income-to-poverty ratio. Since safety-net benefits are closely linked to income cutoffs, with benefits often scaling upward or downward depending on family income (e.g. as with SNAP), the gradient of estimated effects along income-to-poverty ratio cutoffs was particularly revealing. For those living below the poverty line, increased minimum wages had no effect on food insecurity

---

[a] Sabia and Nelson[73] found that in a subpopulation restricted to those less than 30 years old without a high school degree, food insecurity rose when minimum wages increased. These results are likely due to the age restriction, although this study did not find harmful effects among those less than 30 years old.

overall, and resulted in decreased food insecurity among households with children. However, estimates became increasingly more harmful for those with incomes between 100-184% of the poverty line. While these families are above the official poverty cutoff, the cutoff value is low and unadjusted for local cost-of-living: in 2019 a family of four would be considered living in poverty if their household income was less than $25,750.[109] This means that four-person families making up to $47,380 would fall at 184% of the poverty cutoff. Since cost-of-living varies so much by state (and city), it is likely that many of these families could still experience economic insecurity and material hardship. Thus, this gradient of effect may once again suggest a household-level interactive effect with other safety-net program supports – specifically, it is possible that for those with extremely low incomes (i.e. below the poverty cutoff), increased minimum wages complement existing programs to reduce or maintain current levels of food insecurity, as these families are likely to still be eligible for many safety-net benefits; however, at a certain level of income, households will lose existing benefits which may not be offset by the increase in wage. In fact, a study examining how minimum wage policies shift the distribution of family incomes, found that at the fifteenth income percentile, 40% of the increased income due to higher minimum wages was offset by a loss of public assistance.[23] These impacts are also consistent with qualitative research among low-wage workers who often feel that increased wages tend to barely keep up with the cost of living and come at the expense of decreased public benefits.[71,72] While our analysis accounted for state-level accessibility and generosity of the biggest safety net programs, future work should examine household-level interactions with these policies. In particular, a mediation analysis using longitudinal data which examines the moderating effect of net household resources on food insecurity after an increase in minimum wage could be enlightening.

When interpreting results, we considered differences larger than 50 per 10,000 households (or 0.5%) to constitute a meaningful change in food insecurity prevalence, but there were smaller effect estimates that were statistically significant that did not make this cutoff for meaningful change. While small in magnitude, a $1 increase in minimum wage led to increases in food insecurity among some of the most privileged groups: married households with children, households with children who have at least a college degree, and households with income more than 185% of the poverty cutoff. We expected that these groups would be the least likely to be affected by minimum wages, and these harmful findings were unexpected. This may suggest that residual confounding biased the effect estimates for these groups away from the anticipated null result – for example confounding due to household-level factors unrelated to minimum wage increases such as disability, illicit drug use, or other financial shocks. If this is the case, and prevalence difference estimates are systematically shifted upwards from the true value, then this study would have underestimated the protective effects of minimum wage among the most vulnerable households (and underestimated the harmful effects among Black and multiracial households). Alternatively, these surprising, if slight, harmful effects could reflect additional and important heterogeneity within these subpopulations which is worth further exploration. For example, 22% of low-wage workers in the U.S. have an associate's or bachelor's degree[110] and thus there are at least some households with a college degree for which we expect to be impacted.

This study has some limitations. First, while the data were nationally representative, they were not specific to the subset of the population affected by minimum wages. Our research question, however, was about identifying population-level effects and we tried to overcome this limitation by restricting analyses to households with at least one working-aged adult between the ages of 18 to 65 (i.e. those plausibly working) and presenting subgroup effects for those more likely to be affected (i.e. those with lower educational attainment, or with lower income to poverty ratios). Subgroup analyses did indeed illustrate heterogeneity in the effect, though future work could examine the impacts among those directly impacted by minimum wage changes (information we did not have access to in this study). Secondly, due to the nature of the Current Population Survey, we were limited to measuring food insecurity prevalence at a single point in time each year (December). The survey instrument was designed to capture whether a household experienced food insecurity at any point during the preceding calendar year, and thus provides an annual measure of food insecurity prevalence. However, it is well documented that food insecurity is a transient condition, where households often experience recurrent, but not constant, food insecurity.[50] Therefore, temporality between changes in minimum wages and changes in food insecurity status is difficult to establish. Third, this study may be subject to both non-response and self-report biases. We used survey weights to account for systematic differences between those who chose to participate in the Current Population Survey and those who did not. There is also the possibility of outcome and household-level covariate misclassification due to recall errors, social desirability bias, or misunderstanding of survey questions, though these seem unlikely to be differential with respect to the exposure (changes in minimum wages). Finally, while this study examined state-level minimum wage policies – which, when higher, supersede the federal minimum wage policy – some cities and counties mandate even higher minimum wages than the state's rate.[20] This study was unable to take into account the effect of more localized minimum wage laws.

This study also has several notable strengths. Since the data are nationally representative, results provide valuable insights into the effect of minimum wages on changes in population-level food insecurity prevalence and are generalizable to the U.S. overall. Further, the use of the Current Population Survey provided reliable and validated data on food security outcomes for all study years and allowed sufficient sample sizes to examine important heterogeneity in effect in populations defined by race and ethnicity, family structure, educational attainment, and income-to-poverty ratios. Our fixed effects approach allowed us to rigorously account for state-level differences in baseline food insecurity rates and state-specific, time-invariant covariates, to evaluate the state-specific impact of state-level minimum wage increases. We also included a variety of state-time varying confounders to further minimize bias and isolate the effect of interest.

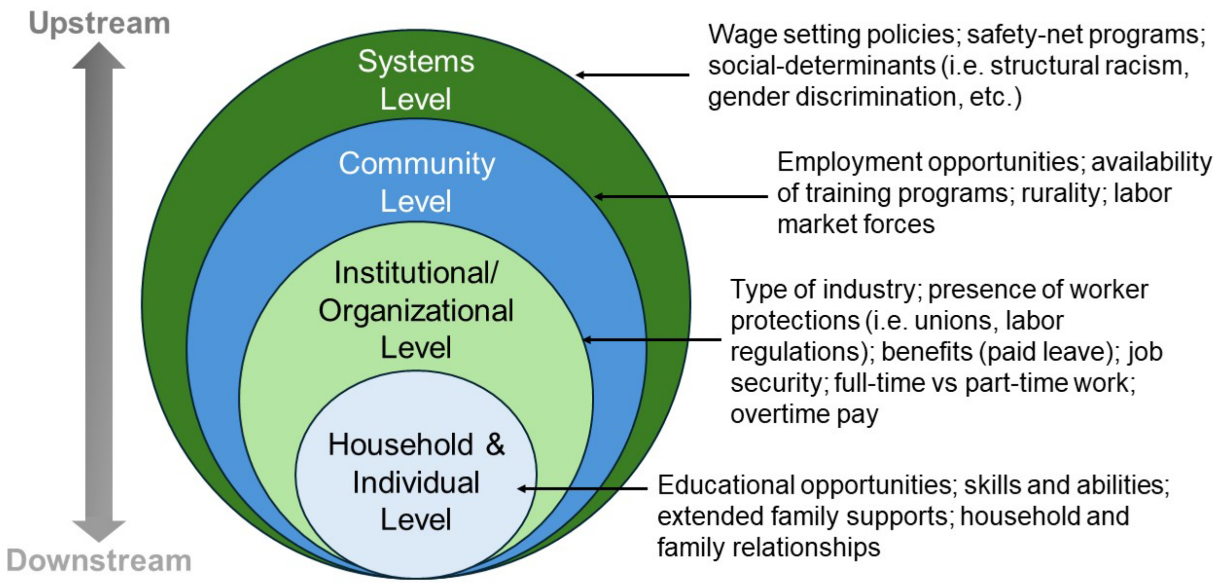
Future research can build on this work by further investigating potential mechanisms by which increased minimum wages may lead to increased food insecurity, especially among Black and multiracial households. It would be useful to examine how minimum wage policies may work with or against other safety net programs (such as SNAP, welfare, etc.) at the household-level to affect food insecurity.

2.5 Conclusions

In this serial cross-sectional study, we examined the impact of state-level minimum wages on changes in household food insecurity prevalence and uncovered important heterogeneity; minimum wages appear to reduce food insecurity prevalence among some marginalized communities such as households whose head has less than a high school diploma, households headed by single women, Indigenous households, and multiracial households with children. At the same time, we found that a $1 increase in minimum wage led to increased food insecurity prevalence among Black and multiracial households overall. A broad structural-level intervention such as state-level minimum wage increases may not be sufficient for reducing all inequities in food insecurity. Further research is needed to elucidate why this may be the case and to identify how such interventions may interact with other targeted safety-net programs to impact household food insecurity.

2.6 Tables and Figures

Figure 2.1. Socio-economic factors impacting food insecurity



Conceptual model of factors impacting food insecurity at all levels, based on the World Health Organization's conceptual framework for tackling social determinants of health inequities,[111]*incorporting determinants of food insecurity*[33,112] *and employment-based income.*[113,114]

Figure 2.2. Trends in food security status between 2002 and 2019 among households with working-aged adults between18-65 years old from the Current Population Survey

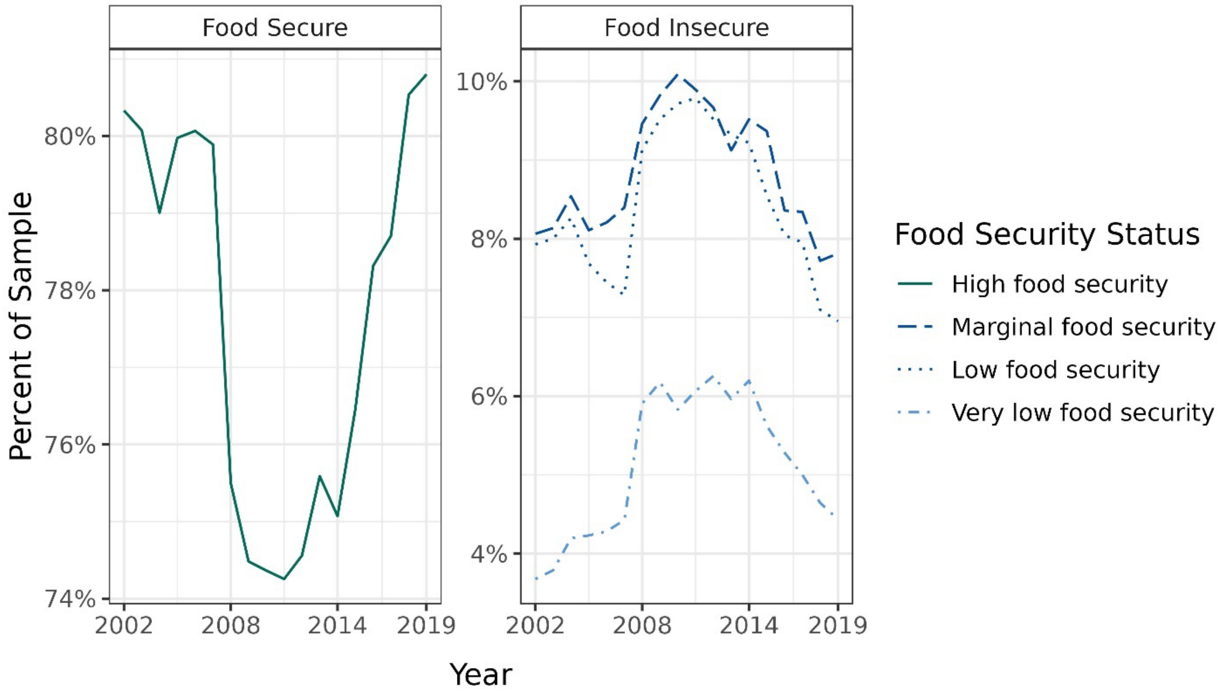
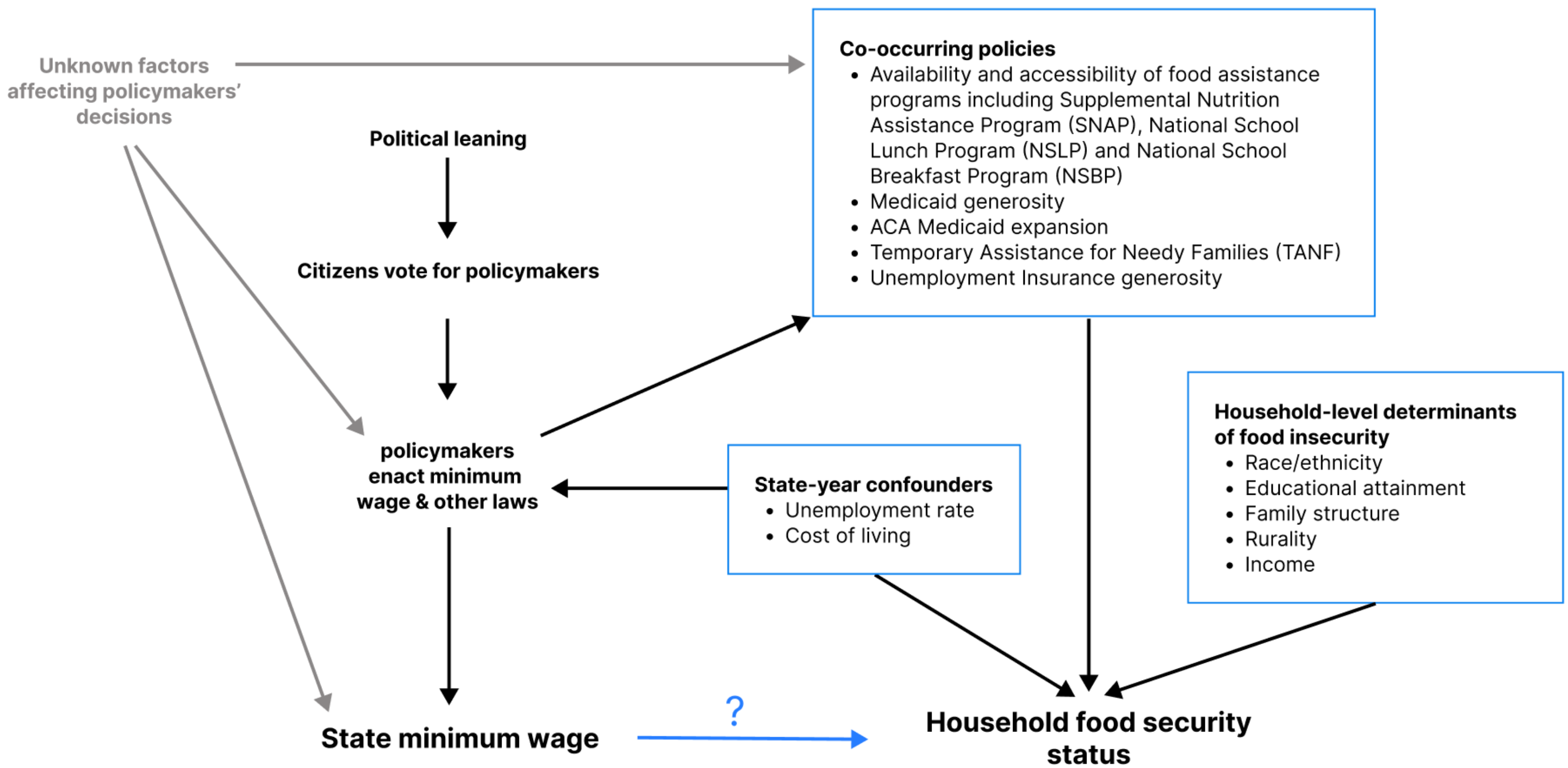


Figure 2.3. Directed acyclic graph depicting key variables determining household-level food security status



Boxed nodes denote variables adjusted for in the analysis including hypothesized confounders (i.e. state-year unemployment rate and cost of living), descendants of confounders (i.e. co-occurring policies such state-year take-up rates of the Supplemental Nutrition Assistance Program and Medicaid generosity), and risk factors for the outcome (i.e. household level demographics such as race and ethnicity and educational attainment).

Table 2.1. Household demographics of study sample, overall and stratified by lower vs. higher minimum wage states

	All households[a]	Households in lower minimum wage states[b]	Households in higher minimum wage states[c]
State of residence	All states	AL*, GA, ID, IN, KS, KY, LA*, MS*, ND, OK, SC*, TN*, TX, UT, VA, WY	AK, AR, AZ, CA, CO, CT, DC, DE, FL, HI, IA, IL, MA, MD, ME, MI, MN, MO, MT, NC, NE, NH, NJ, NM, NV, NY, OH, OR, PA, RI, SD, VT, WA, WI, WV
Number of households	624,770 (100)	173,153 (27.7)	451,617 (72.3)
Food security status			
Food Insecure (%)	139,840 (22.4)	42,423 (24.5)	97,417 (21.6)
Young workers, less than 30 years old (%)	90,390 (15.5)	27,231 (16.8)	63,159 (15.0)
Head of household race/ethnicity			
Non-Hispanic Asian (%)	22,830 (3.7)	3,308 (1.9)	19,522 (4.3)
Non-Hispanic Black (%)	63,484 (10.2)	24,587 (14.2)	38,897 (8.6)
Hispanic (%)	65,788 (10.5)	16,772 (9.7)	49,016 (10.9)
Non-Hispanic Indigenous (%)	7,788 (1.2)	1,934 (1.1)	5,854 (1.3)
Multiracial (%)	9,815 (1.6)	2,346 (1.4)	7,469 (1.7)
Non-Hispanic White (%)	455,065 (72.8)	124,206 (71.7)	330,859 (73.3)
Family Structure			
No children (%)	327,631 (52.4)	90,008 (52.0)	237,623 (52.6)
Married with children (%)	204,193 (32.7)	56,288 (32.5)	147,905 (32.8)
Separated or divorced with children (%)	47,725 (7.6)	14,013 (8.1)	33,712 (7.5)
Male single parent[†] (%)	9,512 (1.5)	2,417 (1.4)	7,095 (1.6)
Female single parent[†] (%)	35,709 (5.7)	10,427 (6.0)	25,282 (5.6)
Head of household educational attainment			
Less than high school	60,401 (9.7)	19,740 (11.4)	40,661 (9.0)
High school diploma or equivalent	171,071 (27.4)	49,983 (28.9)	121,088 (26.8)
Some college	119,451 (19.1)	35,013 (20.2)	84,438 (18.7)
At least a college degree	273,847 (43.8)	68,417 (39.5)	205,430 (45.5)

Table continues on next page

	All households[a]	Households in low minimum wage states[b]	Households in higher minimum wage states[c]
Income to Poverty Ratio[d]	***(n = 136,469)*** [d]	***(n = 37,482)*** [d]	***(n = 98,987)*** [d]
Below poverty cutoff	14,066 (10.3)	4,333 (11.6)	9,733 (9.8)
100-129% of poverty cutoff	6,269 (4.6)	1,889 (5.0)	4,380 (4.4)
130-184% of poverty cutoff	11,902 (8.7)	3,680 (9.8)	8,222 (8.3)
Greater than 185% of poverty cutoff	104,232 (76.4)	27,580 (73.6)	76,652 (77.4)

[a] Households in which there is at least one working aged adult between 18 and 64 years old.

[b] Lower minimum wage states are defined as states which for the duration of the study period: (i) had no state-level minimum wage, (ii) set their state minimum wage to follow the federal standard, or (iii) had minimum wages which fell below the federal floor, thus effectively allowing the federal minimum wage to take effect.

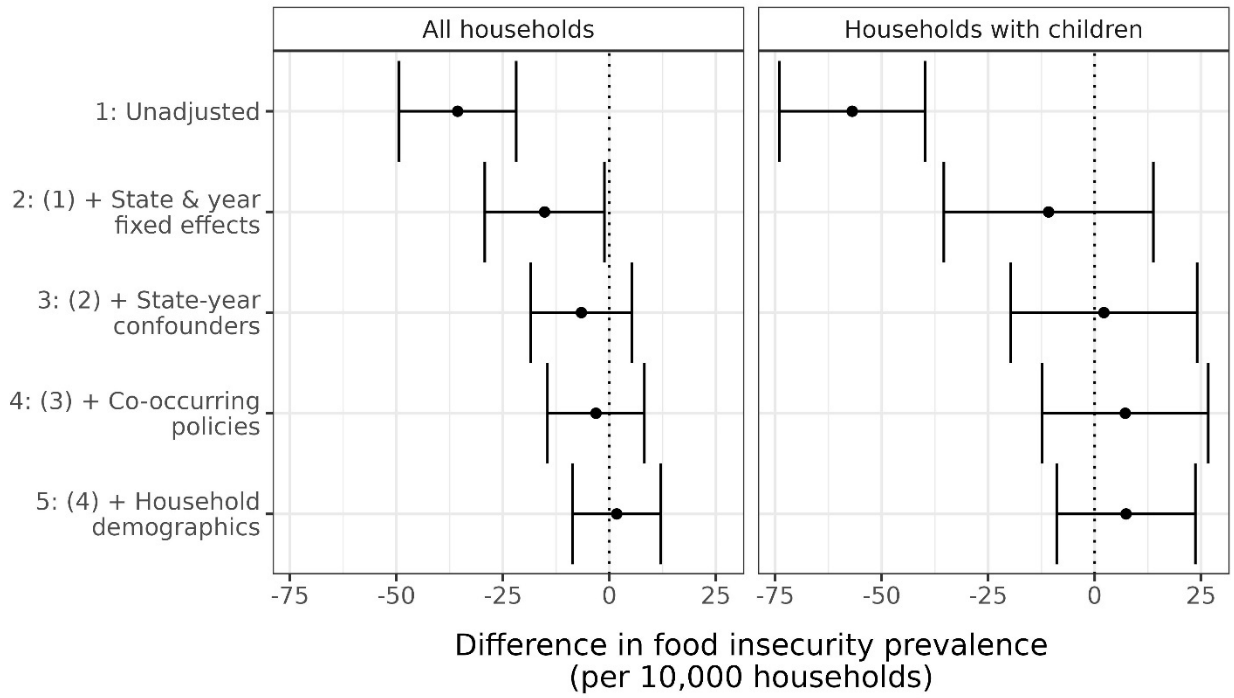
[c] Higher minimum wage states had minimum wages which exceeded the federal minimum wage at least once during the study period.

[d] Restricted sample of households who have detailed income and poverty information (only available for participants who also completed the Current Population Survey's Annual Social and Economic Supplement, approximately 27% of the main sample) and who have at least one working aged adult between 18 and 64 years old.

** Indicates state has no state-level minimum wage.*

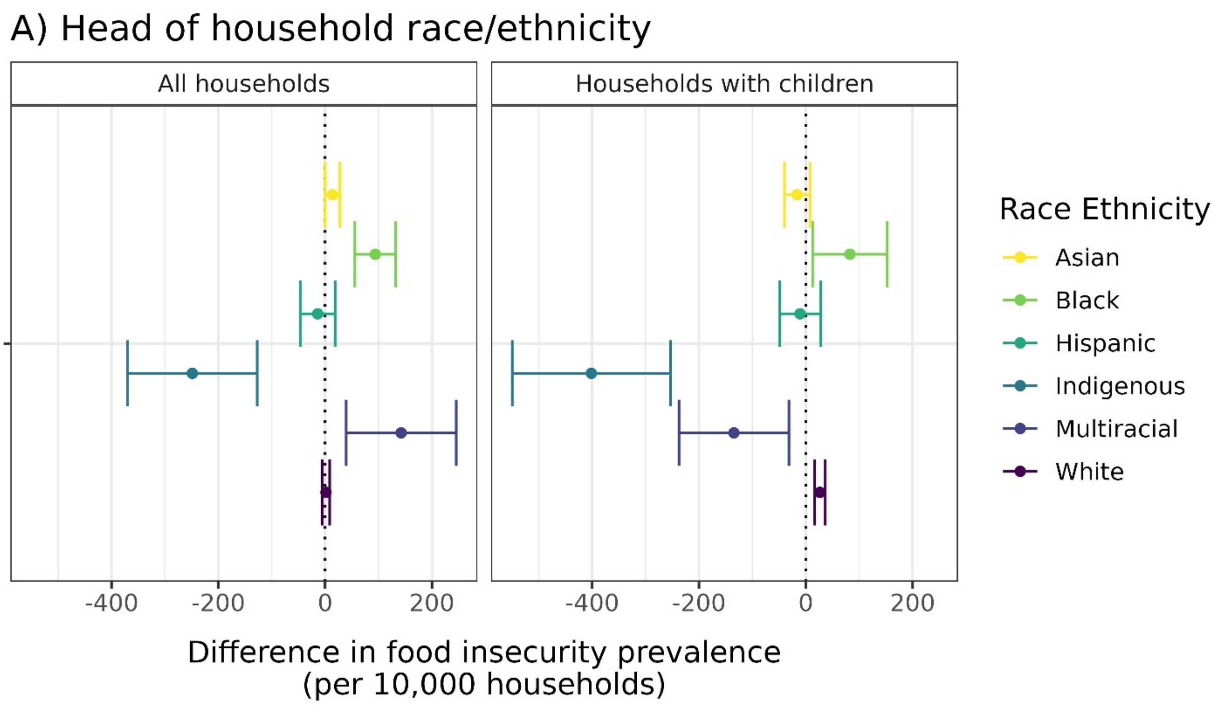
[†] Includes those who have never been married and those who are widowed.

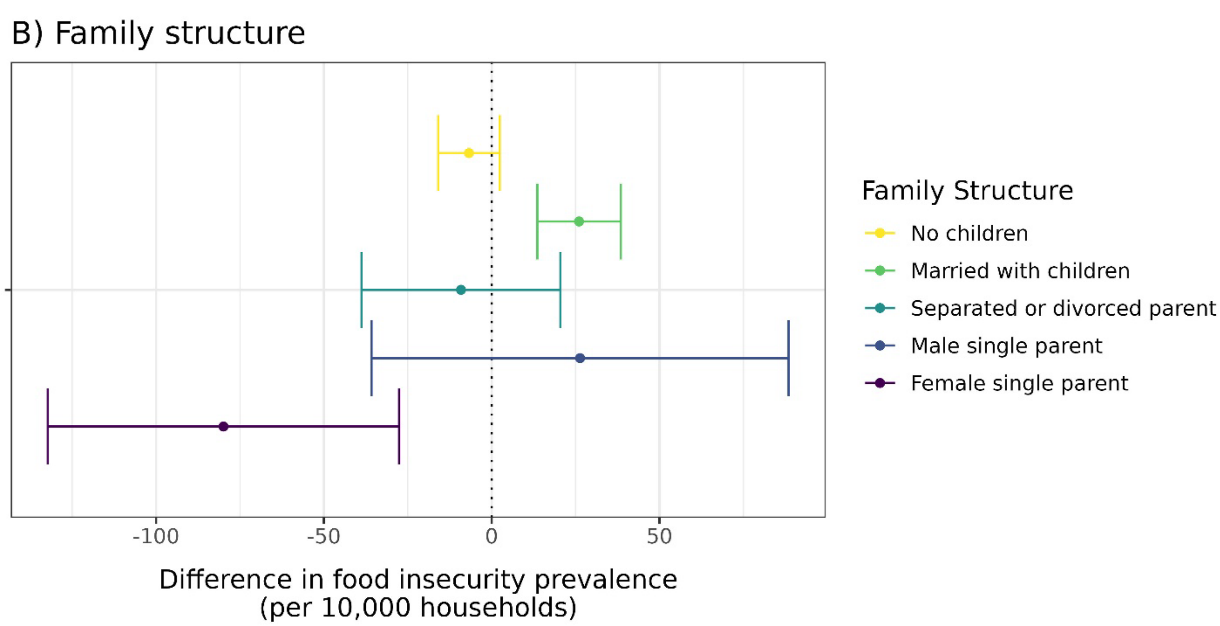
Figure 2.4. Prevalence differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on food insecurity prevalence, separately for all working aged households and those with children



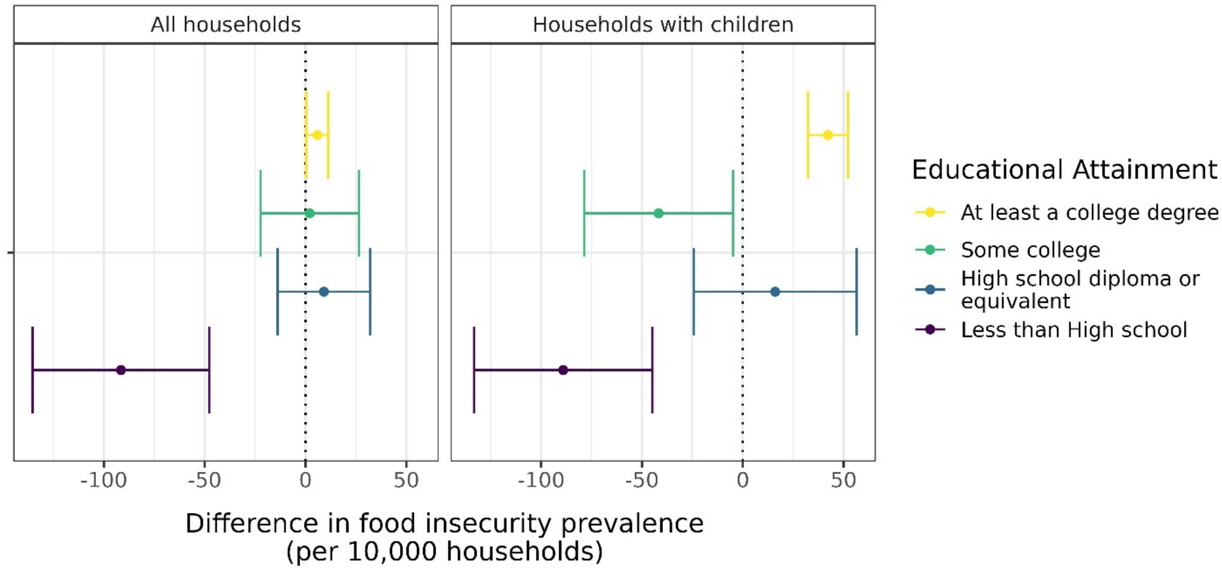
Point estimates and 95% confidence intervals from a linear probability model comparing models with increasing adjustment sets: (1) unadjusted; (2) model 1 plus adjustment for state and year fixed effects; (3) model 2 plus state-year confounders; (4) model 3 plus co-occurring policies; (5) model 4 plus household-level demographics. Standard errors were clustered at the state-level and survey weights were included to account for participant selection factors and non-response.

Figure 2.5. Fully adjusted (Model 5) prevalence differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on food insecurity prevalence, stratified by subpopulations of interest

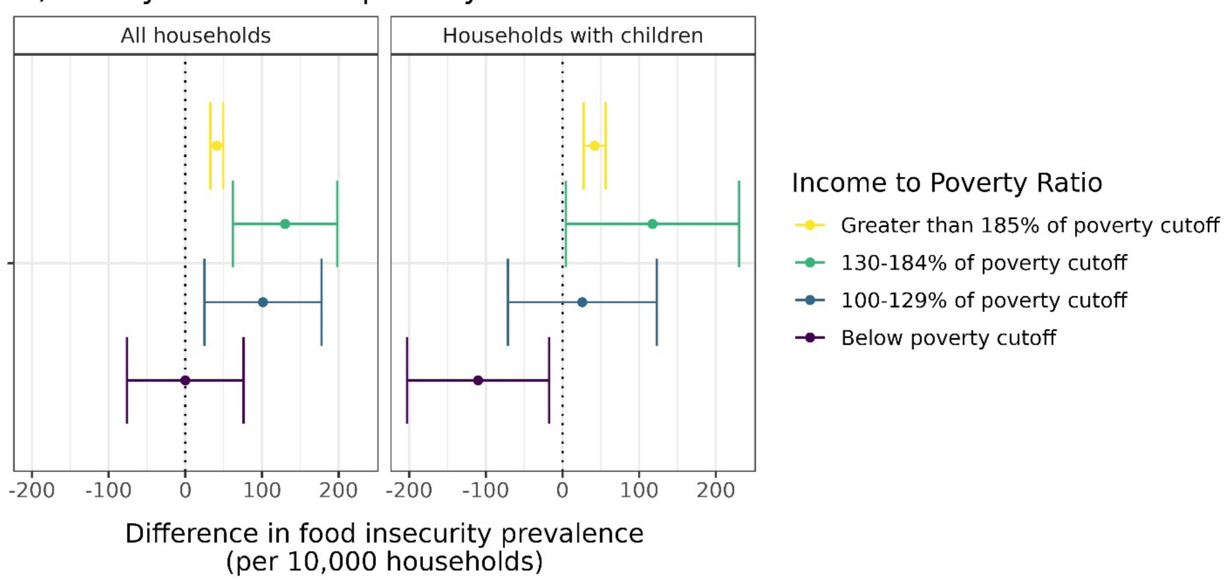




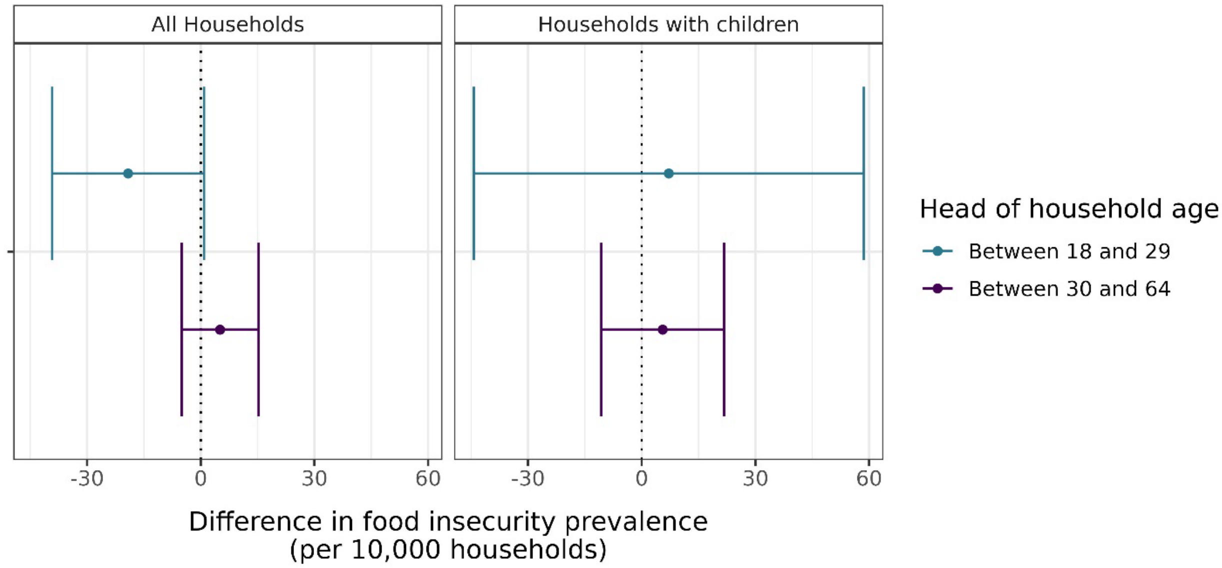
C) Head of household educational attainment



D) Family’s income to poverty ratio



E) Young vs more experienced workers



In each panel, we compare point estimates and 95% confidence intervals among all working aged households and those with children for preferred fully adjusted linear probability model 5 which includes adjustment for state and year fixed effects, state-year confounders, co-occurring policies, and household-level demographics. Standard errors were clustered at the state-level and survey weights were included to account for participant selection factors and non-response. Panel D restricts the main study sample to those with detailed income and poverty information only available for households who also completed the Current Population Survey's Annual Social and Economic Supplement (27.1% of the main sample).

2.7 Supplemental Material

2.7.1 Linking Current Population Survey December supplement to March Annual Social and Economic Supplement

Households are included in a Current Population Survey sample on a 4-8-4 rotation schedule over the course of sixteen months. This means that they are interviewed for four consecutive months, take an eight-month break, and are then interviewed again for another four consecutive months. Thus, we can expect that about a quarter of households interviewed in December will also be interviewed again the following March (i.e., those who first entered the rotation in December).

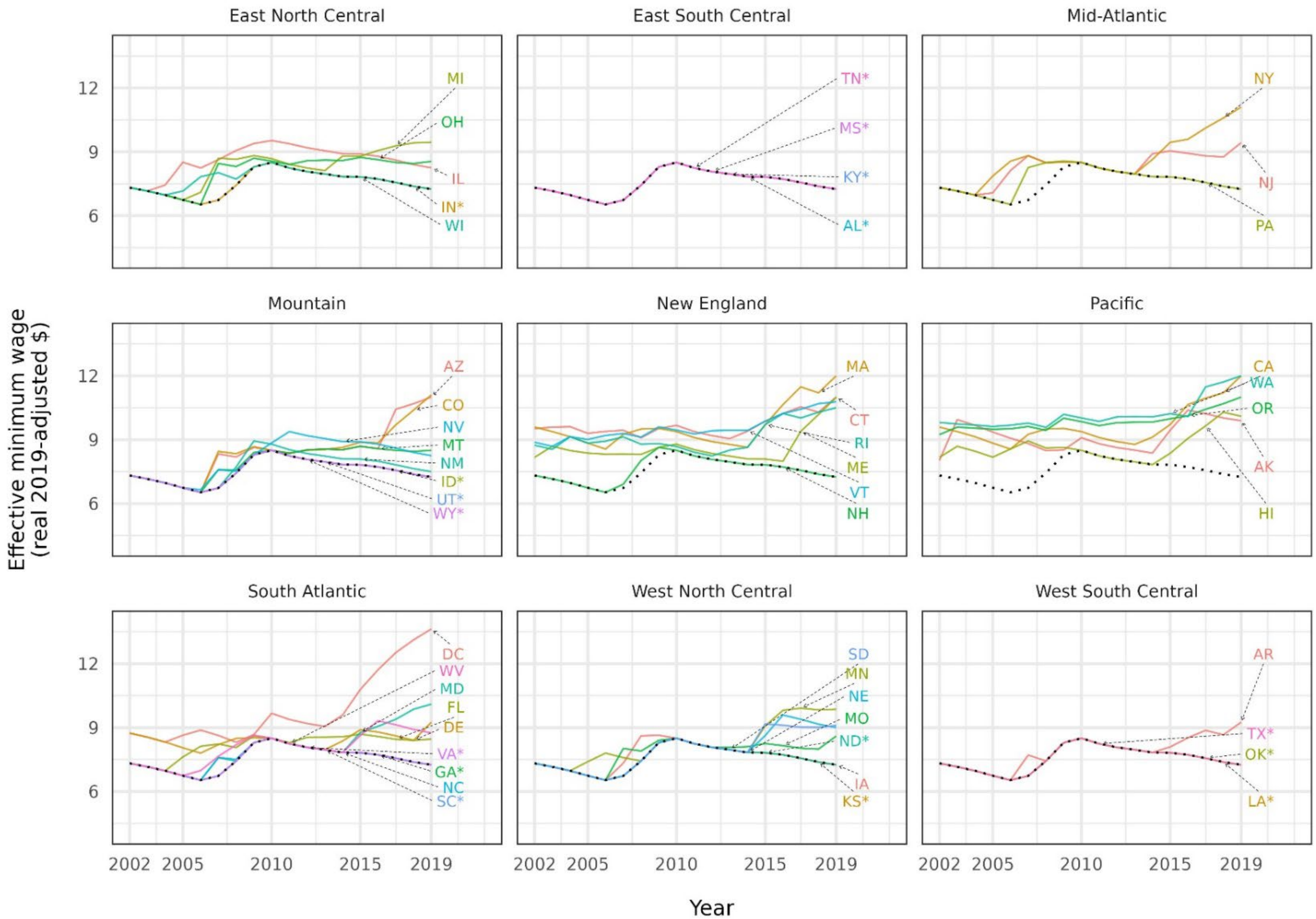
The benefit of linking households across interview months is that, aside from some core questions which are asked every month, different supplements are fielded each month. For example, the U.S. Household Food Security Survey Module (HSFSSM), which assesses detailed information about a household's food security status, is fielded in December, while the Annual Social and Economic Supplements (ASEC), which assesses detailed information on income and poverty status from the previous calendar year, is fielded in March. In fact, the food security information collected from the HSFSSM is used to determine official food insecurity statistics while the social and economic information collected from the ASEC is used to calculate official poverty measures in the United States.

We performed the following steps to link applicable households who completed the HSFSSM with their ASEC responses four months later:

1) Obtain the unique person ID (variable name: CPSIDP) for each head of household in the December Supplement sample. Note that CPSIDP is a variable created by the Integrated Public Use Microdata Series[81] to uniquely identify each survey respondent.
2) Use the CPSIDP to match appliable individuals to their March Supplement in the following year.
3) Obtain the unique ID (variable name: MARBASECIDP) identifying individuals who completed both the March basic monthly survey and the ASEC Supplement survey.
4) Use the MARBASECIDP to match appliable individuals to their ASEC responses.

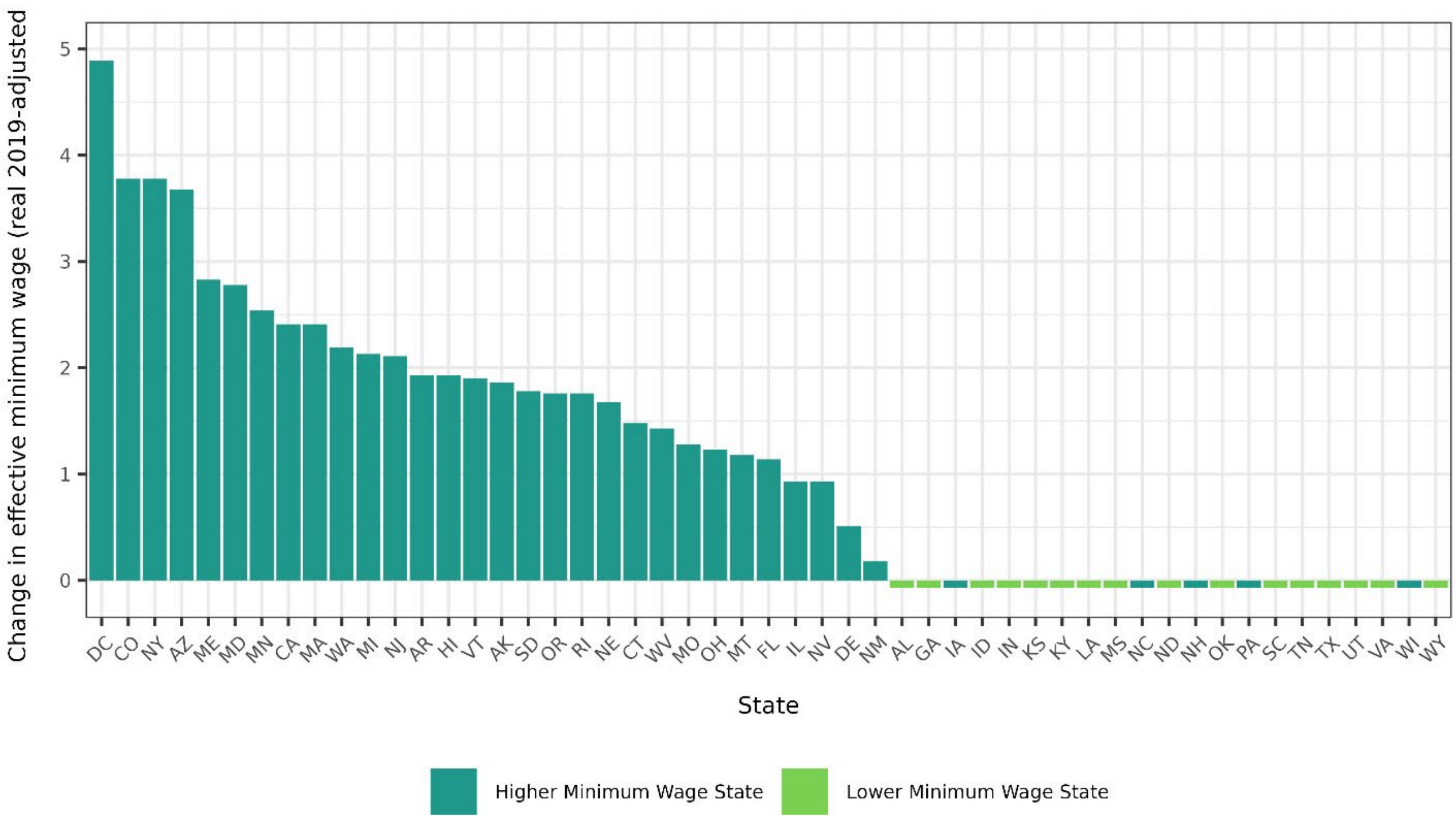
2.7.2 Supplemental Figures and Tables

Supplemental Figure 2.1. Trends in state-level effective minimum wages (solid-colored lines) compared to inflation-adjusted real federal minimum wage (black dotted line), by census division, 2002-2019



** For the duration of the study period, these states either: (i) had no state-level minimum wage, (ii) set their state minimum wage to follow the federal standard, or (iii) had minimum wages which fell below the federal floor, thus effectively allowing the federal minimum wage to take effect.*

Supplemental Figure 2.2. State-specific effective minimum wage change between 2002 and 2019, colored by higher vs lower minimum wage states



Supplemental Table 2.1. Prevalence differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on food insecurity prevalence, separately for all working aged households and those with children

Model	**Difference in food insecurity prevalence per 10,000 households (95% confidence Interval)**	
	All Households ***(n = 624,770)***	**Households with children** ***(n = 297,139)***
(1) Unadjusted	-36 (-49, -22)	-57 (-74, -40)
(2) Model 1 + adjustment for state and year fixed effects	-15 (-29, -1)	-11 (-35, 14)
(3) Model 2 + adjustment for state and year fixed effects + state-year confounders	-7 (-18, 5)	2 (-20, 24)
(4) Model 3 + adjustment for state and year fixed effects + state-year confounders + co-occurring policies	-3 (-15, 8)	7 (-12, 27)
(5) Model 4 + adjustment for state and year fixed effects + state-year confounders + co-occurring policies + household-level demographics	2 (-9, 12)	7 (-9, 24)

Supplemental Table 2.2. Fully adjusted (Model 5) prevalence differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on food insecurity prevalence, stratified by subpopulations of interest

Subpopulation	Sample size All Households (Households with children)	Difference in food insecurity prevalence per 10,000 households (95% confidence Interval)	
		All Households	Households with children
Head of household race/ethnicity			
Non-Hispanic Asian	22,830 (11,990)	14 (0, 28)	-16 (-40, 8)
Non-Hispanic Black	63,484 (31,009)	94 (56, 132)	83 (13, 153)
Hispanic	65,788 (40,997)	-14 (-47, 19)	-11 (-49, 28)
Non-Hispanic Indigenous	7,788 (4,290)	-249 (-370, -127)	-402 (-550, -254)
Multiracial	9,815 (4,648)	142 (39, 245)	-134 (-237, -32)
Non-Hispanic White	455,065 (204,205)	2 (-5, 8)	26 (16, 36)
Family Structure			
No children	327,631	-7 (-16, 2)	-
Married with children	(204,193)	-	26 (14, 38)
Separated or divorced with children	(47,725)	-	-9 (-39, 20)
Male single parent[†]	(9,512)	-	26 (-36, 88)
Female single parent[†]	(35,709)	-	-80 (-132, -28)

Table continues on next page

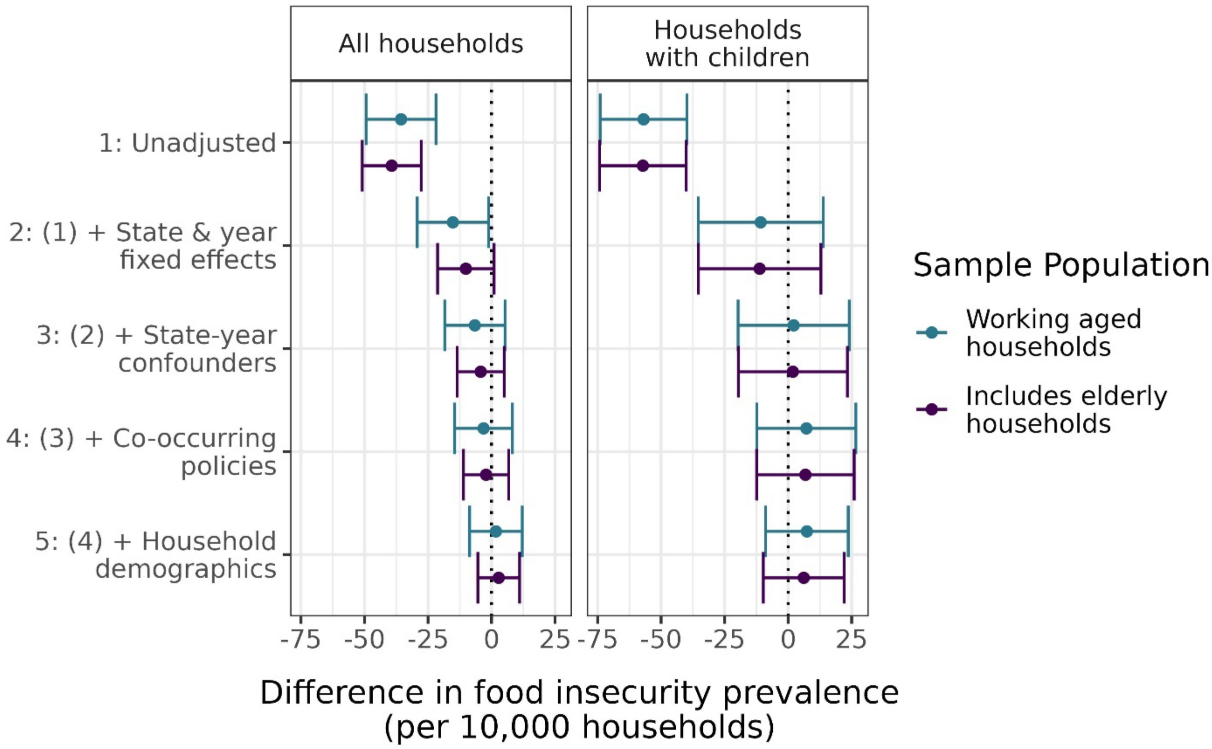
Subpopulation	Sample size All Households (Households with children	Difference in food insecurity prevalence per 10,000 households (95% confidence Interval) All Households	Households with children
Head of household educational attainment			
Less than high school	60,401 (33,402)	-92 (-135, -48)	-89 (-133, -45)
High school diploma or equivalent	171,071 (82,038)	9 (-14, 32)	16 (-24, 56)
Some college	119,451 (55,075)	2 (-22, 27)	-42 (-79, -5)
At least a college degree	273,847 (126,624)	6 (0, 11)	42 (32, 52)
Income to Poverty Ratio*			
Below poverty cutoff	14,066 (6,865)	0 (-76, 76)	-110 (-203, -17)
100-129% of poverty cutoff	6,269 (2,995)	101 (25, 178)	26 (-71, 123)
130-184% of poverty cutoff	11,902 (5,608)	130 (62, 198)	117 (4, 230)
Greater than 185% of poverty cutoff	104,232 (55,353)	41 (33, 49)	42 (28, 56)
Young vs more experienced workers			
Ages 18 to 29	90,390 (32,079)	-19 (-39, 1)	7 (-44, 59)
Ages 30 to 64	493,916 (244,003)	5 (-5, 15)	6 (-11, 22)

Estimates and 95% CIs from preferred fully adjusted linear probability model 5, which includes adjustment for state and year fixed effects, state-year confounders, co-occurring policies, and household-level demographics. Standard errors were clustered at the state-level and survey weights were included to account for participant selection factors and non-response.

* *Restricted sample of households who have detailed income and poverty information (only available for participants who also completed the Current Population Survey's Annual Social and Economic Supplement, approximately 27% of the main sample) and who have at least one working aged adult between 18 and 64 years old.*

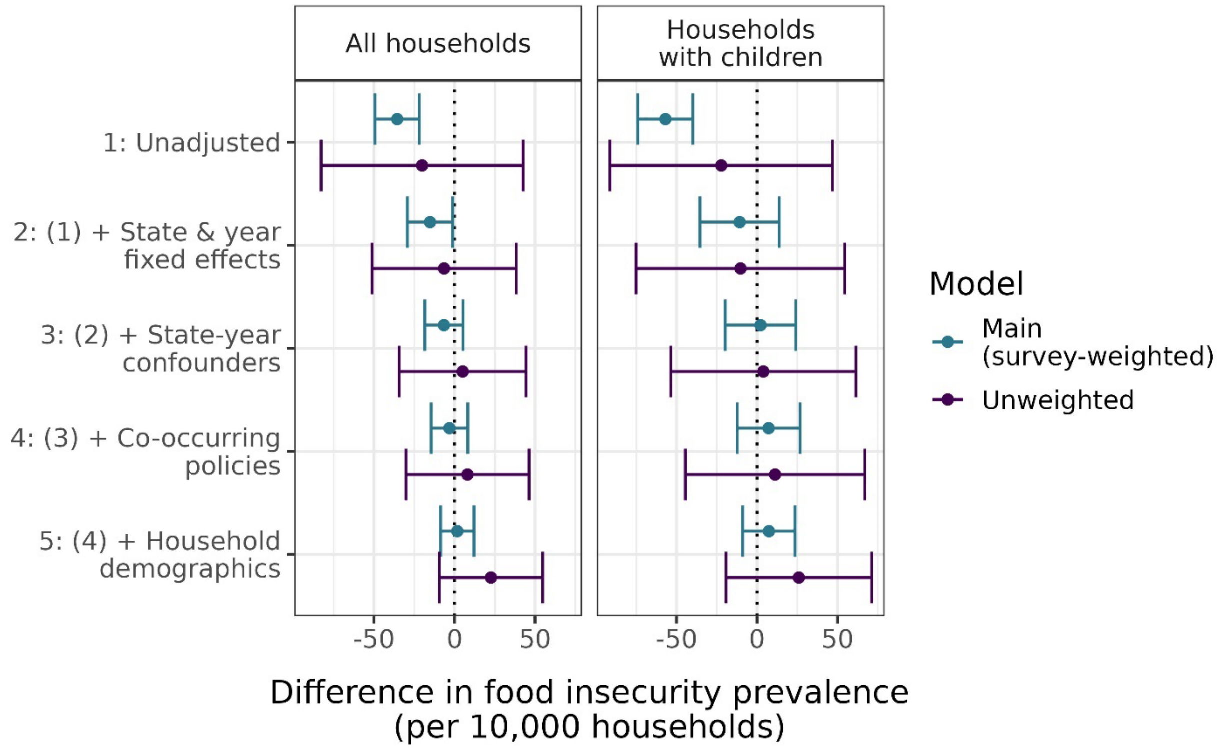
† *Includes those who have never been married and those who are widowed.*

Supplemental Figure 2.3. Prevalence differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on food insecurity prevalence, by sample population working age restrictions.



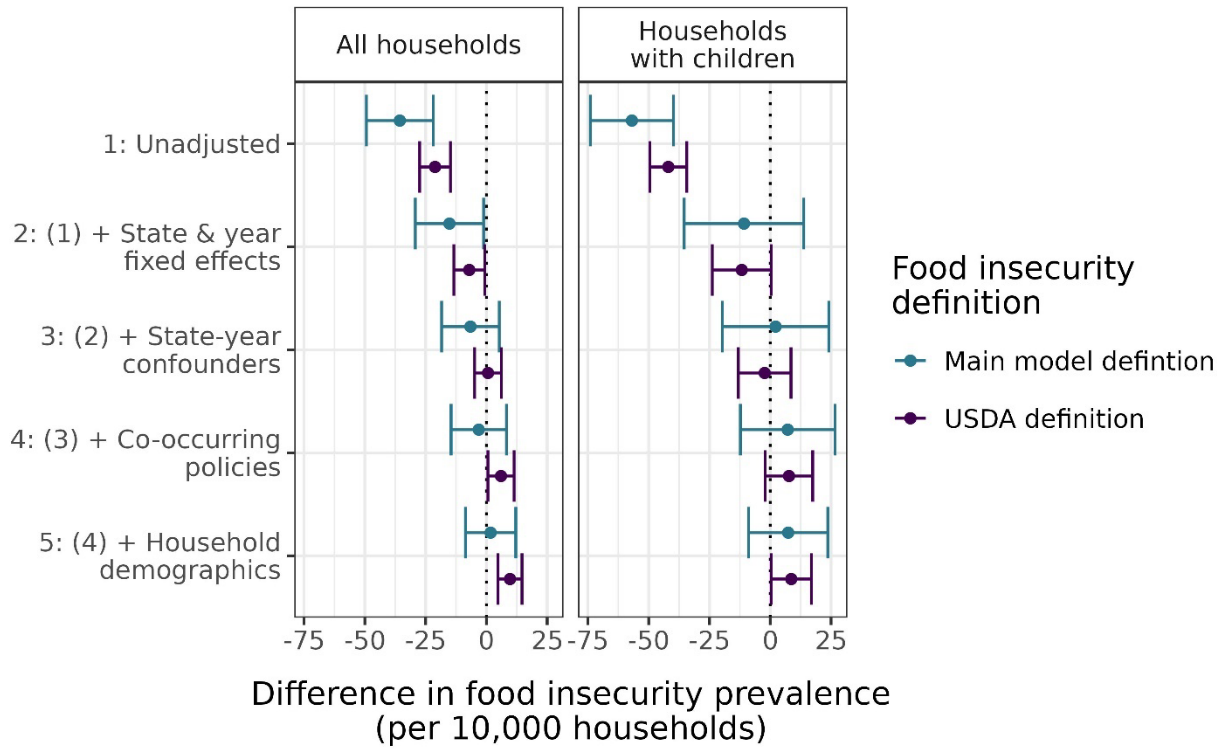
Point estimates and 95% confidence intervals from a linear probability model comparing models with increasing adjustment sets: (1) unadjusted; (2) model 1 plus adjustment for state and year fixed effects; (3) model 2 plus state-year confounders; (4) model 3 plus co-occurring policies; (5) model 4 plus household-level demographics. Standard errors were clustered at the state-level and survey weights were included to account for participant selection factors and non-response. Working aged households restrict to the sample to households with at least one adult between the ages of 18 and 65.

Supplemental Figure 2.4. Prevalence differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on food insecurity prevalence, comparing main survey-weighted analysis to unweighted analysis



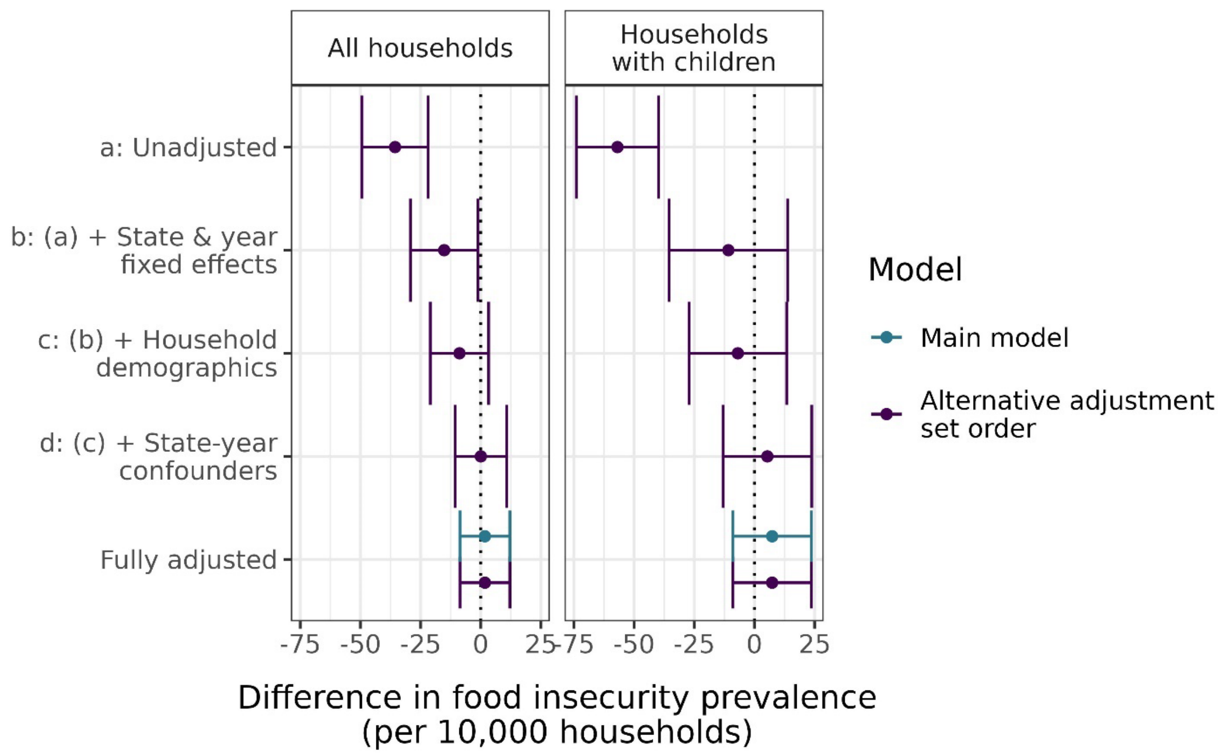
Point estimates and 95% confidence intervals from a linear probability model comparing models with increasing adjustment sets: (1) unadjusted; (2) model 1 plus adjustment for state and year fixed effects; (3) model 2 plus state-year confounders; (4) model 3 plus co-occurring policies; (5) model 4 plus household-level demographics. Standard errors were clustered at the state-level. The main (survey-weighted) model used survey weights to account for participant selection factors and non-response.

Supplemental Figure 2.5. Prevalence differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on food insecurity prevalence, by food insecurity definition.



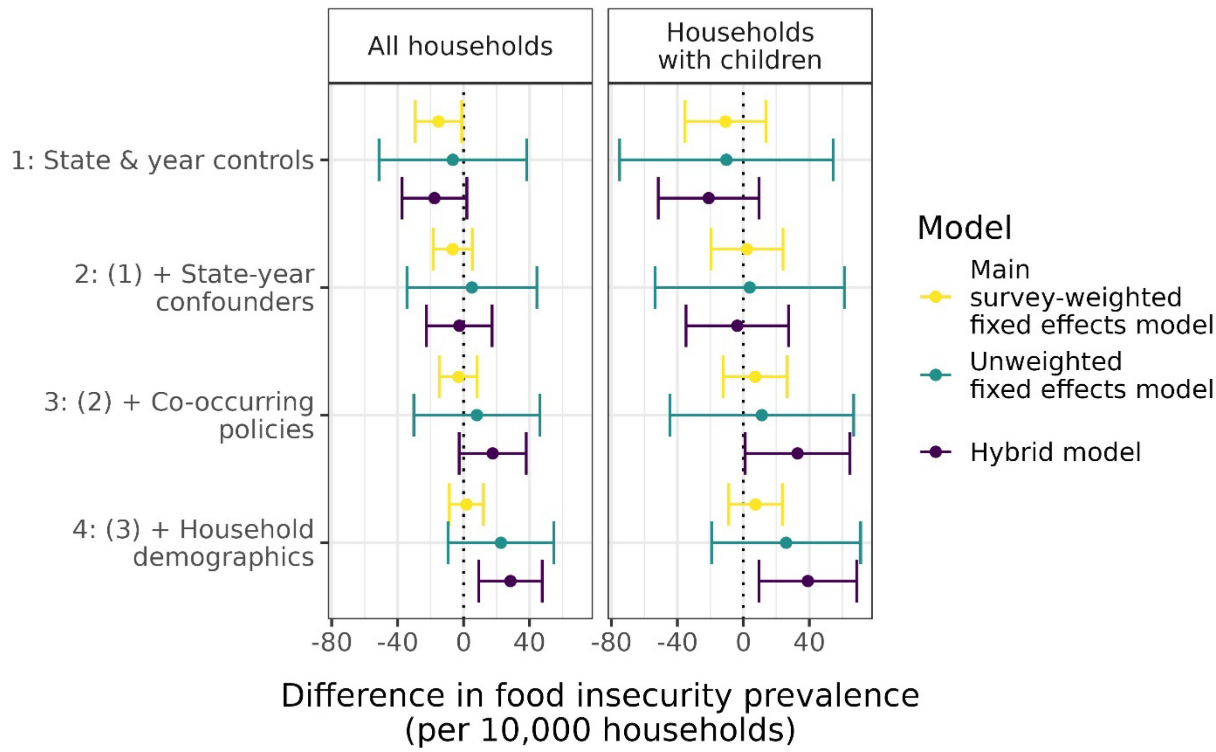
Point estimates and 95% confidence intervals from a linear probability model comparing models with increasing adjustment sets: (1) unadjusted; (2) model 1 plus adjustment for state and year fixed effects; (3) model 2 plus state-year confounders; (4) model 3 plus co-occurring policies; (5) model 4 plus household-level demographics. Standard errors were clustered at the state-level and survey weights were included to account for participant selection factors and non-response. Main model classified households experiencing very low, low, or marginal food security as food insecure and those with high food security as food secure, while the U.S. Department of Agriculture (USDA) definition classified households experiencing very low or low food security as food insecure and those with marginal or high food security as food secure.

Supplemental Figure 2.6. Prevalence differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on food insecurity prevalence, using an alternative adjustment set order



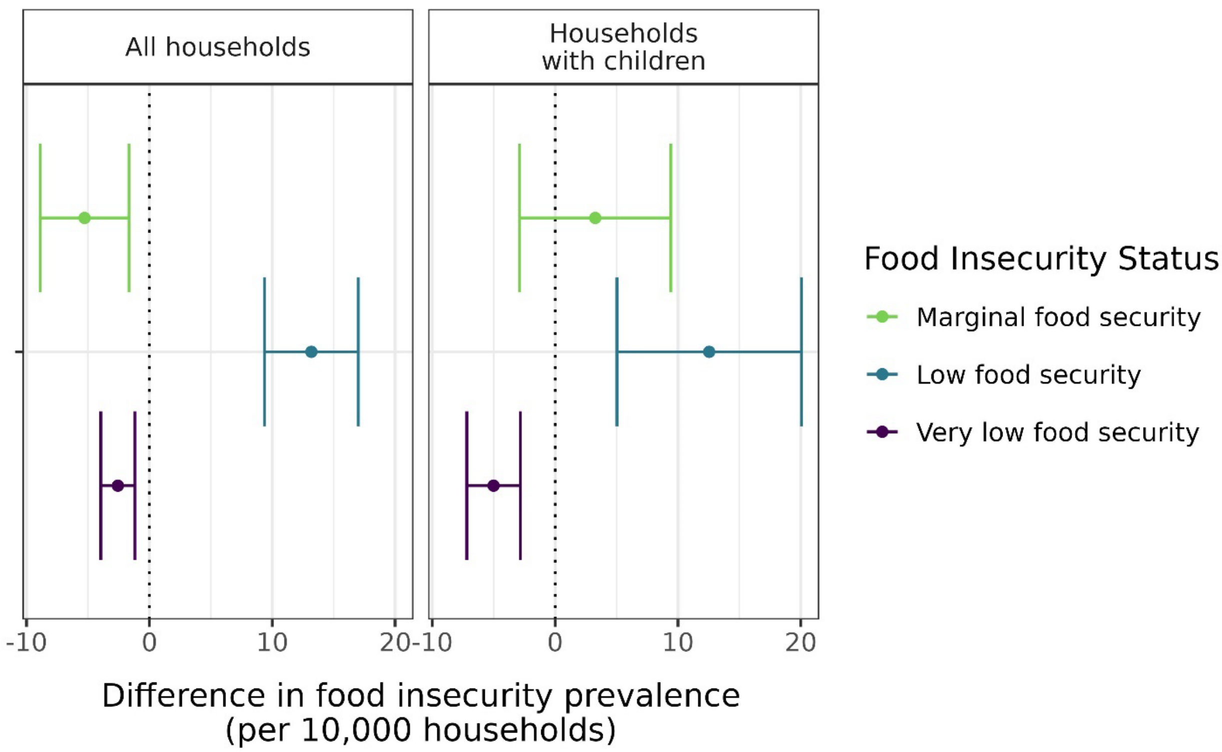
Point estimates and 95% confidence intervals from a linear probability model comparing models with an alternative adjustment set order: (a) unadjusted; (b) model a plus adjustment for state and year fixed effects; (c) model b plus household-level demographics; (d) model c plus state-year confounders; (e) model d plus co-occurring policies (i.e. the fully adjusted model). The fully adjusted model from the alternative adjustment set order is compared with the fully adjusted main model. Standard errors were clustered at the state-level and survey weights were included to account for participant selection factors and non-response in all models.

Supplemental Figure 2.7. Prevalence differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on food insecurity prevalence, comparing main fixed effects model, unweighted fixed effects model, and hybrid model



Point estimates and 95% confidence intervals comparing main survey-weighted fixed effects linear probability model with an unweighted fixed effects linear probability model and a linear hybrid fixed effects model with increasing adjustment sets: (1) adjustment for state and year controls; (2) model 1 plus state-year confounders; (3) model 2 plus co-occurring policies; (4) model 3 plus household-level demographics. State and year controls for the main and unweighted fixed effects models used state and year fixed effects while for the hybrid model, these controls used state-specific minimum wage means and year-specific minimum wage means. The main model included survey weights to account for participant selection factors and non-response while comparison models were unweighted. Standard errors were clustered at the state-level in the main and unweighted fixed effects models while the hybrid model included a state-specific random intercept to account for clustering.

Supplemental Figure 2.8. Fully adjusted (Model 5) prevalence differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on food insecurity prevalence, separately for households experiencing marginal, low, and very low food security.



Point estimates and 95% confidence intervals among all working aged households and those with children for preferred fully adjusted linear probability model 5 which included adjustment for state and year fixed effects, state-year confounders, co-occurring policies, and household-level demographics. Standard errors were clustered at the state-level and survey weights were included to account for participant selection factors and non-response.

Chapter 3: Impacts of state-level minimum wages on food insecurity among households receiving government food assistance (SNAP) benefits

3.1 Introduction

The Supplemental Nutrition Assistance Program (SNAP) is the largest food and nutrition program in the United States (U.S.), serving an average of 33 million individuals annually since 2000.[115] Households with gross monthly income falling below 130 percent of the official poverty line are typically eligible (subject to some other requirements),[116] and those who qualify receive benefits that can be used to purchase most food items available in grocery stores. Monthly benefit amounts are determined by household size and phase out at a benefit-reduction rate of 30 percent of net income, which means that for every additional dollar earned, benefits are reduced by 30 cents.[116] There is consistent evidence that SNAP reduces food insecurity[35–40] – characterized by a household's inability to reliably obtain nutritionally adequate and safe foods in socially acceptable ways – and improves both health and economic outcomes.[41–44]

However, research also indicates that SNAP benefits, which are based on an outdated food plan from the 1970s that no longer represents the most recent dietary recommendations, are insufficient for many families: SNAP benefits often run out before the end of month, and many adult recipients continue to report restricting food intake, compromising nutrition, and not eating so that their children will have enough food.[45–47] Almost one-third of SNAP recipients also obtain charity food from food banks and pantries,[48] highlighting an urgent gap between benefits and need. Further, at current benefit levels, participants are often unable to purchase the quantity and quality of nutritious foods, such as fresh fruits and vegetables, needed for a healthful life.[46,49] Food-insecure adults who are unable to obtain adequate nutrients are at a higher risk for some of the most common and chronic health conditions – such as diabetes, hypertension, depression, and poor sleep outcomes.[117] Food insecurity is especially detrimental to the development of children, associated with increased risk of anemia, asthma, lower nutrient intake, cognitive problems, depression and anxiety, and poorer general health overall.[117] Unfortunately, in 2019, almost half of households receiving SNAP benefits remained food-insecure.[50]

Since SNAP eligibility is based solely on financial need, the program reaches a wide range of low-income households, including those with children, elderly, disabled, and/or unemployed individuals. Despite this, most SNAP households report some degree of employment: almost 75% of households with children and a non-disabled adult had at least one household member who worked during a typical month of SNAP participation.[118] This means that a large portion of SNAP households are subject to labor market policies and conditions, including the minimum wage. Minimum wage laws may be set at the federal, state, and local level, with the highest wage value taking precedence for the majority of employees.[86] There is a vast literature studying the effects of minimum wages on employment, wages, earnings, and various health-related outcomes. Research examining the relationship between minimum wages and food insecurity, however, is limited and suggests no overall effect of increased minimum wages on population-level food insecurity,[73–76] with slight harmful effects for workers under 30 years old who have less than a high school degree.[73] We are unaware of any national-level study examining the impact of increased minimum wages on food insecurity among the SNAP population, despite the fact that this population experiences high levels of food insecurity. Increased wages have the potential to provide SNAP households with additional money to spend on food, thus decreasing food insecurity. At the same time, due to the built-in benefit reduction rate, monthly SNAP benefits also decrease proportionally to increased income, potentially netting out any benefit of increased wages. Further still, administrative burdens associated with SNAP recertification, particularly after an income change, could lead some households to lose their benefits entirely even if they are still eligible,[119,120] which could result in increased food insecurity. Therefore, the effect of increased minimum wages on food insecurity for SNAP households is unclear.

Two studies examining the effect of a single local minimum wage increase on the food insecurity, stress, and diet-related health of low-wage workers in Minneapolis between 2018-2020 found no evidence of either a beneficial or adverse effect.[74,76] Neither study focused on SNAP recipients specifically, though one examined changes in SNAP participation and found that trends were not different in Minneapolis compared to a control city with no minimum wage increase.[74] The second study observed a decrease in SNAP benefits as wages rose.[76] It is worth noting that the time period of both studies coincided with temporary increases in SNAP benefits, flexibility, and eligibility as part of the Families First Coronavirus Response Act (during the COVID-19 pandemic) which makes their findings difficult to generalize further.[121] Qualitative work examining the effects of increased minimum wage has documented negative side effects for SNAP and other low wage workers. In one study, SNAP recipients reported experiencing frequent and destabilizing changes to their benefits when their income changed, and said that they were unable to reap the benefits of increased wages due to complex financial tradeoffs.[72] In particular, participants reported that wage increases were often accompanied by other changes such as fluctuating work hours, increases in commute time and corresponding childcare costs, and higher food prices, all of which combined to offset the extra wage income.[72] A separate qualitative study examining perceptions on wages, food acquisition, and well-being among low-income workers supported the notion that minimum wage increases were barely enough to offset annual increases in cost-of-living expenses.[71] That study found that more than a third of surveyed low-income workers associated increases in income with decreases in government assistance benefits (including SNAP) and/or increases in prices for basic needs and cost-of-living.[71] Taken together, it is plausible that an increase in minimum wages could have no effect or lead to increased food insecurity among some SNAP households.

Moreover, while poverty and low-income are the strongest determinants of food insecurity, [33,34] not all low-income households are food insecure: in 2019, only one third of households with incomes below 130 percent of the poverty line (many of which would be eligible for SNAP) were food insecure.[77] Rates of household food insecurity vary significantly by race and ethnicity, educational attainment, and family structure;[34,50,78,79] While 10.5% of all U.S. households experienced food insecurity in 2019, food insecurity rates were much higher among non-Hispanic Black- and Hispanic-headed households (19.1% and 15.6% respectively),[50] households with children (13.6%),[50] and households headed by single women (28.7%).[50] In 44% of all food-insecure households, the most educated adult household member had a high school level education or less.[31] These same populations are also disproportionately more likely to be minimum wage workers: both Hispanic and Black workers are overrepresented in the low-wage workforce; females account for 54% of low-wage workers; and the largest proportion of low-wage workers are between the ages of 25 to 50 with no more than a high school diploma, almost half of which are raising children.[17] We therefore expect there to be differences in the effect of minimum wages on food insecurity among SNAP households based on these household demographics.

This study aimed to identify the effect of increases in minimum wages on food insecurity among SNAP recipients and explore whether the effect varied by household demographics such as race and ethnicity, educational attainment, and family structure.

3.2 Data and Methods

3.2.1 Sample

The U.S. Current Population Survey is the largest, national, population-representative survey assessing food insecurity in the U.S. and provides official estimates of food insecurity prevalence each year. It uses a multistage, stratified sample of the civilian, noninstitutionalized U.S. population, with strata designed to represent diverse geographic, economic, and demographic features, and to provide accurate measures of both demographic and labor force characteristics. Households are interviewed for four successive months, take an eight-month break, and are then interviewed for another four consecutive months before exiting the sample. Annual food security status is assessed during the December supplement of the Current Population Survey. The December supplement also includes detailed information on household food spending and nutrition program participation, including SNAP.

In this study, we leveraged data on households which were in the sample for two consecutive Decembers. We used the Integrated Public Use Microdata Series[81] to gather data on households who participated in the December supplement of the Current

Population Survey between 2002 and 2019 (599,204 unique households), and linked households across two consecutive years to create a longitudinal dataset. We chose 2002 as the study start since that was the year the Current Population Survey began assessing food insecurity every December, and 2019 as the study end point to avoid confounding by exogenous factors associated with the COVID-19 pandemic in 2020.[82] We included households who had two consecutive years of data with known food security status and SNAP participation information for both years (67,826 households). To identify SNAP households, we restricted the population to those who had received SNAP benefits during their first interview year, regardless of whether they received benefits in their second year, since minimum wage increases may impact later participation in SNAP (15,853 households). We also excluded 8 households living in group quarters (i.e., college dormitories, military barracks, group homes, missions, and shelters) because they were sampled as individuals and were not linked to other family members or household information. Compared to all households participating in the December supplement of the Current Population Survey, households in the final analytic sample had a higher proportion of non-Hispanic Black and Hispanic heads of household, fewer elderly households (over age 65), a higher proportion of separated, divorced and single parents (especially single female parents), and lower educational attainment (see Supplemental Material for further details).

3.2.2 Outcome: food security

The December supplement of the Current Population Survey assesses household food security status via the U.S. Household Food Security Survey Module. It includes 18 questions for households with children under the age of 18 years and 10 questions for households without children (Appendix A). Based on responses to this survey, households are classified as having high, marginal, low, or very low food security. We used this classification to create a binary food security variable which categorizes households with high food security as experiencing food security and remaining households as experiencing food insecurity. While this definition of food insecurity differs slightly from the official U.S. Department of Agriculture (USDA) definition – where households experiencing marginal food security are considered food secure[83] – current research documents that the experience of those with marginal food security is more similar to the experience of food insecure households rather than food secure households.[84] We therefore used the broader definition of food insecurity for our main and subpopulation analyses and assessed alternate classifications in sensitivity analyses.

3.2.3 Exposure: state minimum wage

We obtained information on federal- and state-specific minimum wages from the University of Kentucky Center for Poverty Research[85] and confirmed dates of any change in minimum wage via government websites. To calculate the effective minimum wage, we performed the following steps: First, we calculated a weighted average of minimum wages in each federal- and state-year to account for the proportion of the year each minimum wage value was in effect. Second, for state-years where the federal minimum wage is higher than the state minimum wage, we replaced the state-specific dollar value with the federal dollar value, since the majority of employees are entitled to such under The Fair Labor Standards Act.[86] Finally, we used the consumer price index[87] to convert the nominal state-year minimum wage to real 2019 dollars, and used this value as the state-year effective minimum wage.

3.2.4 Covariates

We created a directed acyclic graph (Figure 3.1) to illustrate hypothesized confounders (i.e. state-year unemployment rate and cost of living), descendants of confounders (i.e. co-occurring safety-net policies such as Medicaid and unemployment insurance generosity), and risk factors for the outcome (i.e. household level demographics such as race and ethnicity and educational attainment).

3.2.4.1 State-year confounders

We considered state- and year-specific unemployment rates and cost of living as time-varying confounders (Figure 3.1). We hypothesized that unemployment rates[85] may be used as an important economic indicator by policy-makers when deciding which programs to fund, and research shows that increases in unemployment lead to increases in food insecurity at the state-level.[90–93] We used housing costs – estimated by the median rent for a two bedroom apartment averaged across all counties in a state-year from the U.S. Department of Housing and Urban Development[95] and converted to real 2019 dollars using the consumer price index[87] – as a proxy for cost of living since housing is a major fixed expense impacting a household's ability to afford food.[91,94] Both of these variables were lagged one year to ensure temporality.

3.2.4.2 State- and time-varying safety-net policies

We also gathered data on several other state- and time-varying safety-net policies (Figure 3.1), since these are descendants of unobservable other factors impacting policymakers' decisions to increase the minimum wage (and enact other policy changes). We focused on programs whose accessibility and generosity may play a role in determining a family's food security status. First, we characterized the availability and accessibility of the National School Breakfast program by computing the ratio of students participating in school breakfasts[85] to those participating in school lunches[85] (since the National School Lunch Program is more ubiquitously available across states and commonly used as a benchmark for the National School Breakfast program, this measure captures state- and year-specific programmatic changes in school breakfast relative to the more stable school lunch program[93]). Medicaid is another poverty alleviation program whose eligibility rules, administrative burdens, and benefits we hypothesized could impact household-level food insecurity.[122,123] We thus obtained state-year Medicaid generosity scores,[97] an index of these programmatic characteristics. Note that neither school meal programs nor Medicaid directly impact household income or SNAP eligibility. Similarly, welfare (also known as Temporary Assistance for Needy Families) generosity, which often provides cash aid to families, may impact food security status without affecting SNAP eligibility (it also does not count as income for tax purposes). We measured welfare generosity using the cash benefit amount for a two-person family,[85] converted to real 2019 dollars using the consumer price index.[87] Finally, we obtained data on state-year unemployment insurance characteristics[98] and calculated unemployment insurance generosity as the maximum available benefit dollar amount times the maximum available number of weeks, converted to real 2019 dollars using the consumer price index.[87] Unlike the other safety-net policies, unemployment insurance benefits does impact income as well as resulting SNAP eligibility.

3.2.4.3 Household demographics

Household-level food security (and income) may also be influenced by a family's demographic characteristics such as race and ethnicity, educational attainment and living in a metropolitan area[34,50,78,79] (Figure 3.1). While these characteristics are not confounders of the exposure-outcome relationship, they are predictors of the outcome and were defined via the following variables in Current Population Survey: head of household's race and ethnicity (Non-Hispanic Asian; Non-Hispanic Black; Hispanic; Non-Hispanic Indigenous [which includes those who identified as American Indian/Alaska Natives and Hawaiian/Pacific Islanders]; Multiracial; Non-Hispanic White); head of household's educational attainment (less than high school; high school diploma or equivalent; some college; and college degree [which includes those with associate's, occupational, bachelor's, and advanced degrees]); household's rurality (lives in a central city; lives outside a central city; does not live in a metropolitan area; unknown).

3.2.5 Statistical analysis

First, we calculated descriptives on the study population and effective minimum wage changes over time. For these statistics, we distinguish between states who have a policy-mandated state-specific minimum wage change (i.e. changes in minimum wage not due to inflation but due to policy) compared to ones that did not. Descriptive statistics were weighted by survey weights, except for baseline summary statistics in Table 3.1 which provide sample sizes.

We estimated prevalence differences (PD) for the effect of a $1 increase in minimum wage on the change in food insecurity prevalence among households who received SNAP benefits via a linear probability model.[88,89] We included four nested models with increasing adjustment sets: (1) unadjusted; (2) model 1 plus adjustment for state and year fixed effects to eliminate confounding by unmeasured factors that varied across states and by shared secular trends respectively; (3) model 2 plus state- and time-varying confounders and safety-net policies; and (4) model 3 plus household-level demographics to increase precision (Equation 3.1). We calculated 95% confidence intervals (95%CI) using robust standard errors clustered at the household level. Household food security scale weights were included to account for participant selection factors and non-response. We calculated separate effects among all households, elderly households whose head is 65 years of age or older, working-aged households without children, and working-aged households with children. We defined working-aged households as those whose head of household was between the ages of 18 and 64.

$$y_{ist} = \beta_0 + \beta_1 * MW_{st} + \beta_2 * \mathbf{S}_s + \beta_3 * \mathbf{Y}_t + \beta_4 * \mathbf{X}_{st} + \beta_5 * \mathbf{P}_{st} + \beta_6 * \mathbf{H}_{ist} + \varepsilon_{ist} \qquad \text{(Eq. 3.1)}$$

Where: y_{ist} is a binary variable denoting whether or not household i in state s in year t is food insecure (y = 1 indicates food insecure): β_0 is the intercept; MW_{st} is the effective minimum wage for state s in year t with β_1 denoting the policy effect of interest; $\mathbf{S}_s$ is a vector of indicator variables for each state s with β_2 indicating each state fixed effect; $\mathbf{Y}_t$ is a vector of indicator variables for each year t with β_3 indicating each year fixed effect; $\mathbf{X}_{st}$ is a vector of the state- and time-varying confounders (Figure 3.1) with β_4 representing the coefficients on these confounders; $\mathbf{P}_{st}$ is a vector of the state-and time-varying safety-net policies (Figure 3.1) with β_5 representing the coefficients on these policies; $\mathbf{H}_{ist}$ is a vector of the household-level demographics determining income and food insecurity status (Figure 3.1) with β_6 representing the coefficients on these factors; and ε_{ist} is residual household-level variation. Households were restricted to those receiving SNAP benefits in their first year of observation.

3.2.6 Subpopulation analyses

Since low-income and SNAP eligibility are not enough on their own to induce food insecurity, we investigated heterogeneity in the effect of minimum wages on food insecurity among marginalized and vulnerable subgroups defined by factors such as race and ethnicity, educational attainment, and family structure (i.e. single parents). Since previous studies have found negative impacts of minimum wage on young adults under the age of 30, we were also interested in examining whether effects were different among this population. We performed the following stratified analyses using the same four adjustment sets as the main model:

a) *Head of household race/ethnicity* (Non-Hispanic Asian; Non-Hispanic Black; Hispanic; Non-Hispanic Indigenous; Multiracial; Non-Hispanic White).

b) *Head of household educational attainment* (less than high school; high school diploma or equivalent; some college; college degree).

c) *Family structure for working aged families with children*, as defined by the head of household's marital status and gender (married with children; separated or divorced parents; male single parent; female single parent).

d) *Young vs more experienced workers*, defined by head of household's age (18-29 years old; 30-64 years old).

Subpopulation analyses a) and b) were restricted to working-aged households with and without children and exclude elderly households due to small sample size. Note that household demographics under investigation were not used in the Model 4 adjustments.

3.2.7 Sensitivity analyses

To assess the robustness of our findings and evaluate the potential impact of analytic decisions, we completed several sensitivity analyses.

First, while survey weights adjust for non-response, survey design, and oversampling, and are necessary for estimating population-representative statistics, they may not be necessary when estimating measures of effect, and may also lead to decreased precision.[99,124] We therefore conducted a sensitivity analysis without applying weights to assess how point estimates and precision are affected by weighting. Main analyses used the household food security scale weight (variable name: "FSHWTSCALE", the preferred weight when analyzing food security status[81]), but we also performed analyses using the food security supplement (FSS) weight for household-level analyses (variable name: "FSSUPPWTH") as well as the basic monthly household weight (variable name: "HWTFINL") to determine if results were sensitive to the specific household weight used.

Second, we used an alternative definition of food insecurity where those experiencing marginal food security were classified as being food secure, in line with the official USDA definition of food insecurity. We expected that this alternative classification would underestimate true food insecurity and thus estimates of the effect of minimum wages on food insecurity may be attenuated compared to when those with marginal food security are classified as being food insecure.

Third, to determine if results were specific to the fixed effects model specification, and to address any potential bias that may be induced in such models (See Appendix B for discussion), we ran three alternative linear models using the same four adjustment sets as the main fixed effects analysis: (i) a generalized estimating equation (GEE) with an exchangeable correlation structure (equation 3.2); (ii) a linear mixed effects model with household-specific random intercepts (equation 3.3); and (iii) a linear hybrid fixed effects model with household-specific random intercepts (equation 3.4). Instead of state fixed effects, the hybrid model in (iii) used state-specific minimum wage means to control for fixed differences between states that may be correlated with minimum wages.[103] Similarly, instead of year fixed effects, the hybrid model in (iii) used year-specific minimum wage means to control for differences between years that may be correlated with the exposure.[103] This sensitivity analysis did not permit survey weights and so we used the unweighted linear probability (fixed effects) model as a comparison. While all three alternative models are designed to account for clustering and repeated measures, there are differences in their interpretations. GEE models are marginal models, intended to provide population average effects, and are generally robust to misspecification of the correlation structure. On the other hand, mixed effects and hybrid models utilize both between household and within household variation to generate conditional effect estimates and assume that unobserved factors affecting the outcome are uncorrelated with the observed explanatory variables in the model. If results are not sensitive to model form, we would expect that conclusions from each of these models would not be materially different from that of the unweighted analysis.

$$y_{ist} = \beta_0 + \beta_1 {*} MW_{st} + \beta_2 {*} \boldsymbol{S}_s + \beta_3 {*} \boldsymbol{Y}_t + \beta_4 {*} \boldsymbol{X}_{st} + \beta_5 {*} \boldsymbol{P}_{st} + \beta_6 {*} \boldsymbol{H}_{ist} + \varepsilon_{ist} \qquad \text{(Eq. 3.2)}$$

Where: y_{ist} is a binary variable denoting whether or not household i in state s in year t is food insecure (y = 1 indicates food insecure): β_0 is the intercept; MW_{st} is the effective minimum wage for state s in year t with β_1 denoting the policy effect of interest; $\boldsymbol{S}_s$ is a vector of indicator variables for each state s with β_2 indicating each state fixed effect; Y_t is a vector of indicator variables for each year t with β_3 indicating each year fixed effect; $\boldsymbol{X}_{st}$ is a vector of the state- and time-varying confounders (Figure 3.1) with β_4 representing the coefficients on these confounders; $\boldsymbol{P}_{st}$ is a vector of the state-and time-varying safety-net policies (Figure 3.1) with β_5 representing the coefficients on these policies; $\boldsymbol{H}_{ist}$ is a vector of the household-level demographics determining income and food insecurity status (Figure 3.1) with β_6 representing the coefficients on these factors; and ε_{ist} is residual household-level variation. Households were restricted to those receiving SNAP benefits in their first year of observation.

$$y_{ist} = \beta_{00} + \beta_{0i} + \beta_1 {*} MW_{st} + \beta_2 {*} \boldsymbol{S}_s + \beta_3 {*} \boldsymbol{Y}_t + \beta_4 {*} \boldsymbol{X}_{st} + \beta_5 {*} \boldsymbol{P}_{st} + \beta_6 {*} \boldsymbol{H}_{ist} + \varepsilon_{ist} \qquad \text{(Eq. 3.3)}$$

Where: y_{ist} is a binary variable denoting whether or not household i in state s in year t is food insecure (y = 1 indicates food insecure): β_{00} is the intercept representing the grand mean; β_{0i} is the random effects household-specific intercept; MW_{st} is the effective minimum wage for state s in year t with β_1 denoting the policy effect of interest; $\boldsymbol{S}_s$ is a vector of indicator variables for each state s with β_2 indicating each state fixed effect; $\boldsymbol{Y}_t$ is a vector of indicator variables for each year t with β_3 indicating each year fixed effect; $\boldsymbol{X}_{st}$ is a vector of the state- and time-varying confounders (Figure 3.1) with β_4 representing the coefficients on these confounders; $\boldsymbol{P}_{st}$ is a vector of the state-and time-varying safety-net policies (Figure 3.1) with β_5 representing the coefficients on these policies; $\boldsymbol{H}_{ist}$ is a vector of the household-level demographics determining income and food insecurity status (Figure 3.1) with β_6 representing the coefficients on these factors; and ε_{ist} is residual household-level variation. Households were restricted to those receiving SNAP benefits in their first year of observation.

$$y_{ist} = \beta_{00} + \beta_{0i} + \beta_1 {*} MW_{st} + \beta_2 {*} \overline{MW}_s + \beta_3 {*} \overline{MW}_t + \beta_4 {*} \boldsymbol{X}_{st} + \beta_5 {*} \boldsymbol{P}_{st} + \beta_6 {*} \boldsymbol{H}_{ist} + \varepsilon_{ist} \qquad \text{(Eq. 3.4)}$$

Where: y_{ist} is a binary variable denoting whether or not household i in state s in year t is food insecure (y = 1 indicates food insecure): β_{00} is the intercept representing the grand mean; β_{0i} is the random effects household-specific intercept; MW_{st} is the effective minimum wage for state s in year t with β_1 denoting the policy effect of interest; $\overline{MW}_s$ is the average minimum wage for state s across all years with β_2 indicating the coefficient on this term; $\overline{MW}_t$ is the *average minimum wage for year t across all states with β_3 indicating the coefficient on this term; $\boldsymbol{X}_{st}$ is a vector of the state- and time-varying confounders (Figure 3.1) with β_4 representing the coefficients on these confounders; $\boldsymbol{P}_{st}$ is a vector of the state-year co-occurring policies (Figure 3.1) with β_5 representing the coefficients on these policies; $\boldsymbol{H}_{ist}$ is a vector of the household-level demographics determining food insecurity status (Figure 3.1) with β_6 representing the coefficients on these factors; and ε_{ist} is residual household-level variation. Households were restricted to those receiving SNAP benefits in their first year of observation.*

Lastly, since it is more common in economics to present estimates adjusted for household-level factors before estimates adjusted for other confounders, we present an alternative order of adjustment sets: (a) unadjusted; (b) model a plus adjustment for state and year fixed effects; (c) model b plus household-level demographics; and (d) model c plus state-year confounders and safety-net policies (i.e. the fully adjusted model). We did not expect fully adjusted estimates or confidence intervals to be impacted.

3.2.8 Post-hoc analyses

In our main analysis we found that results were sensitive to the inclusion of survey weights as well as the definition of food insecurity (i.e. whether those experiencing marginal food security were classified as food secure or food insecure). We therefore performed all subpopulation analyses using no weights and using the alternative definition of food insecurity to provide further insights. We also added analyses which excluded households experiencing marginal food security to determine whether the effects of minimum wage on food insecurity were primarily driven through changes among those experiencing marginal food security. If this were the case, we would expect to see mainly null effects among models excluding households with marginal food security.

We also found implausibly large effect estimates among the subpopulation of households with an Asian head of household. We therefore performed additional descriptive and analytic analyses among this group to investigate potential factors impacting results (see Supplemental Material).

All analyses were performed using R version 4.3.3. This study was not considered human subjects research and no institutional review board approval was required.

3.3 Results

3.3.1 Descriptive statistics

Between 2002 and 2019, two-fifths (39.4%) of households in the study sample lived in a state with a state-specific policy-mandated minimum wage increase between consecutive years of observation. These households, however, experienced only a 5-cent increase in effective minimum wage on average, due to adjustment for inflation and concurrent federal minimum wage increases (Figure 3.2). Effective minimum wage changes across consecutive years ranged from a decrease of $0.35 to an increase of $1.92. Households in states with a policy-mandated increase in minimum wage experienced an average increase of $0.35 in effective minimum wage. However, despite having a state-level policy increase, 20% of these states still saw a year-over-year decrease in effective minimum wage (due to inflation).

Unweighted baseline study sample characteristics are described in Table 3.1: those living in states with vs. without a policy-mandated increase in minimum wage were similar with respect to percentage of young workers (under the age of 30), head of household race and ethnicity, head of household educational attainment, and household composition. There were a slightly higher proportion of Black households living in states without a policy-mandated minimum wage increase (25.3%) compared to those in states with a minimum wage policy increase (17.8%). Less than a fifth (17.7%) of all SNAP households had an elderly household head 65 years or older, and about a half of all households (51%) were working aged (between 18 and 65 years old) with children. More than half of the entire sample (55%) had a non-Hispanic White head of household, and the majority of households (67%) had a household head whose highest level of education was a high school diploma or less.

A large proportion of SNAP recipients in the study sample experienced food insecurity (Figure 3.3): less than a third of all households (28.1% across all years) reported high food security during the study period (defined as “food secure” for main analyses), while remaining households reported some level of food insecurity. Elderly households reported the highest levels of food security with an average of 37.5% reporting high food security across all years (compared to 24.8% of working aged households and 27.2% of households with children). Working aged households without children reported the highest levels of very low food security (30.8% on average, compared to 16.8% of elderly households and 17.7% of households with children). Working aged households with children reported the highest levels of low food security (32.4% on average, compared with 23.6% of elderly households and 25.7% of households without children). All households experienced a similar level of marginal food security (between 18.7 and 22.7% on average).

3.3.2 Results from main model analysis

In our main analysis, we found that state-level minimum wages had no impact on the prevalence of household food insecurity among SNAP households overall (Figure 3.4, Supplemental Table 3.1). Unadjusted Model 1 estimates were null [PD = 9 per 10,000 households, 95%CI = (-11, 29)]. The addition of state and year fixed effects (Model 2) shifted estimates slightly and decreased precision but did not alter conclusions [PD = -23 per 10,000 households, 95%CI = (-68, 22)]. Adjusting for state-year confounders and safety-net policies (Model 3) as well as household demographics (Model 4) did not meaningfully change the null estimates for the overall SNAP population [Model 4 PD = -13 per 10,000 households, 95%CI = (-60, 33)].

Fully adjusted (Model 4) estimates stratified by age and presence of children revealed disparate effects. A $1 increase in state-level minimum wage led to an estimated decrease in food insecurity prevalence of 103 per 10,000 households among working aged households with children [95%CI = (-169, -38)], while no effect of state-level minimum wages on food insecurity was found among working aged SNAP households without children [PD = 30 per 10,000 households, 95%CI = (45, 104)]. Conversely, a $1 increase in state-level minimum wage led to an estimated increase in food insecurity prevalence of 180 per 10,000 households among elderly (65 years and older) SNAP recipients [95%CI = (71, 288)]. Adjusted models 2 through 4 showed similar effects within all sample populations.

3.3.3 Results from subpopulation analyses

When we analyzed subpopulations defined by race and ethnicity, family structure, educational attainment, and younger vs. more experienced workers, we observed heterogeneity in the effect of minimum wages on SNAP household food insecurity prevalence (Figure 3.5, Supplemental Table 3.2). Out of the 28 fully adjusted (Model 4) stratified analyses, we found statistically significant (alpha = 0.05) effects in 15 subpopulations; by chance alone, we expected at most two of these models to have statistically significant results.

Fully adjusted Model 4 estimates stratified by race and ethnicity estimated that among working aged households without children, a $1 increase in state-level minimum wage led to: a reduction in the prevalence of food insecurity among Asian households [PD = -4,201 per 10,000 households, 95%CI of (-4,857, -3,546), see Supplemental Material for further investigation of these implausibly high effect estimates], Hispanic households [PD = -274 per 10,000 households, 95%CI = (-472, -94)], and White households [PD = -152 per 10,000 households, 95%CI = (-463, -86)]; no change in food insecurity prevalence among Indigenous households [PD = -105 per 10,000 households, 95%CI = (-376, 165)]; and an increase in food insecurity prevalence among both Black [PD = 289 per 10,000 households, 95%CI = (155, 423)] and Multiracial households [PD = 365 per 10,000 households, 95%CI = (123, 608)]. For working aged households with children, we found no effect of minimum wages on food insecurity prevalence among most racial-ethnic groups, except for Asian households where minimum wages were estimated to be beneficial [PD = -394 per 10,000 households, 95%CI = (-739, -50)] – though this effect disappeared in further analyses which accounted for data anomalies within this subpopulation (see Supplemental Material for further details) – and multiracial households where minimum wages were estimated to be harmful [PD = 894 per 10,000 households, 95%CI = (516, 1,271)].

For working aged households with at least a college degree, increases in minimum wage were estimated to be beneficial, regardless of whether there were children in the household [PD = -208 per 10,000 households without children, 95%CI = (-381, -36); PD = -274 per 10,000 households with children, 95%CI = (-451, -98)]. Minimum wage increases were also estimated to be helpful for working aged households with children who had less than a high school education [PD = -252 per 10,000 households, 95%CI = (-370, -135)]. However, we found that for working aged households without children who had some college credits, a $1 increase in minimum led to an estimated increase in food insecurity prevalence of 462 per 10,000 households [95%CI = (341, 584)]. All remaining households were unaffected by changes in minimum wage.

The specific impact of state-level minimum wages on food insecurity prevalence for working aged families with children also depended on the parents' marital status: a $1 increase in state-level minimum wage was estimated to decrease food insecurity prevalence by 279 per 10,000 households [95%CI: (-389, -169)] for working aged families with married parents and by 201 per 10,000 households [95%CI: (-316, -87)] for households headed by single female parents, while it was estimated to increase food insecurity prevalence by 279 per 10,000 households for those headed by single male parents [95%CI = (24, 534)], and by 179 per 10,000 households for separated or divorced parents [95%CI = (53, 305)].

When stratifying by younger vs. more experienced workers, we found no effect of minimum wages on the food insecurity of those less than 30 years old [PD = -146 per 10,000 households without children, 95%CI = (-407, 115); PD = -76 per 10,000 households with children, 95%CI = (-257, 104)] and more experienced workers (between the ages of 30 and 64) without children [PD = 63 per 10,000 households, 95%CI = (-15,141)]. Among more experienced workers with children, a $1 increase in minimum wage led to an estimated decrease in food insecurity prevalence of 83 per 10,000 households [95%CI: (-149, -17)], which aligned with our estimates among all working aged households with children.

3.3.4 Results from sensitivity analyses

Results were not materially altered when alternative survey weights were used and point estimates in unweighted analyses were also similar to the main survey-weighted analysis (Supplemental Figure 3.5). However, confidence intervals were significantly wider for unweighted analyses (see Appendix C for discussion) and included the possibility of no effect of minimum wages on food insecurity for elderly households and working aged households with and without children. Results were not sensitive to the fixed effects model specification; we found similar point estimates and confidence intervals using the GEE, linear mixed effects, and hybrid fixed effects models as we did in the (unweighted) fixed effects model (Supplemental Figure 3.7).

Results were, however, sensitive to the definition of food insecurity; treating those with marginal food security as being food secure, per the official USDA definition, changed effect estimates and conclusions (Supplemental Figure 3.6). While the effect of state-level minimum wages on food insecurity prevalence remained null for SNAP households overall, fully adjusted (model 4) effect estimates among working aged households shifted when those with marginal food security were considered food secure: for households without a children a $1 increase in minimum wage led to an increase in food insecurity (as opposite to no change in food insecurity), and for households with children, there was no change in food insecurity (as opposed to a reduction of food insecurity). Interestingly, the effect of minimum wages on food insecurity among elderly SNAP households was reversed; in fully adjusted model 4, an increase in minimum wage led to a decrease in food insecurity prevalence for this population when those with marginal food security were considered food secure. Models which excluded households experiencing marginal food security indicated no effect of minimum wages on food insecurity for all household types, with effect estimates that generally fell between main model and USDA model food insecurity definition estimates.

3.3.5 Results from post-hoc analyses

Given that main model conclusions were altered when analyses were unweighted and when alternative definitions of food insecurity were used, we also compared subpopulation analyses using these alternative specifications (Supplemental Figures 3.8 - 3.14). Overall, Model 4 unweighted analyses resulted in large confidence intervals that crossed the null for all subpopulation categories (except for Asian households without children, whose effects remained implausibly large). Using the USDA definition of food insecurity also altered fully adjusted Model 4 conclusions for some subpopulations (namely: Indigenous households with and without children, Hispanic households with and without children, Multiracial households with children, households without children holding a college degree, households with children having a high school diploma, single parent households of both genders, and households between the ages of 30 and 64 with and without children), though the direction of the change was not consistent. Similarly, excluding those with marginal food security altered conclusions from main model analysis for some subpopulations (namely: Indigenous households without children, Hispanic households with and without children, households with children having a high school diploma, and single male parent households).

3.4 Discussion

In this study, we found that the impact of state-level minimum wages on food insecurity among SNAP recipients depended on household characteristics such as age (elderly vs working aged), family structure (including presence of children and marital status of parents), race and ethnicity, and educational attainment. In some cases, results were also sensitive to whether those experiencing marginal food security were classified as food secure or food insecure, indicating that increases in minimum wage may primarily impact food insecurity in some groups by altering the food security status of households experiencing marginal food security. About a fifth of our study population experienced marginal food security throughout the duration of the study, indicating that they were anxious about or had difficulties obtaining enough food with the money available to them (i.e. answering 1-2 questions of the food security supplement in Appendix A in the affirmative). Our main definition of food insecurity was sensitive to whether a household answered 0 questions in the affirmative (food secure) or more than 0 (food insecure), whereas for the USDA's official definition, this threshold is 2 (food secure) or more than 2 (food insecure). Differences in effect estimates were expected as the two definitions are sensitive at different thresholds. Indeed, when we excluded those with marginal food security from the analysis, effect estimates tended to fall in-between estimates from the main model definition and the estimates from the model using the USDA definition of food insecurity.

We observed no effect of minimum wages on SNAP food insecurity prevalence overall, a finding that aligns with past research on low-wage workers.[74,76] However, when examining subgroup-specific effect estimates, we found that increased minimum wages led to a decrease in food insecurity prevalence for households with children, suggesting that state-level minimum wage policies could serve as an investment for low-income families with children. It is possible that these households are bolstered by other safety-net programs aimed at supporting families with children, such as the Earned Income Tax Credit, Child Tax Credit, school meal programs, and the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC).[125,126,127(chap3),128] Such programs typically have higher income eligibility cutoffs compared to SNAP and may thus provide crucial support when income rises to offset any corresponding reduction of SNAP-specific benefits. Since these programs are largely aimed at families with children, this type of additional support would be unavailable for working aged households without children, for whom we found no impact of minimum wages on food insecurity prevalence. The null results we found among households without children quantitatively support qualitative work which highlights that, for most low-wage workers, minimum wage increases only account for increases to the cost of living.[71,72] It is plausible that for this population, increased income just barely makes up for the corresponding reduction of SNAP benefits and, as a result, food insecurity remains unchanged.

For elderly SNAP households over the age of 65, we found that increased minimum wages led to an increase in food insecurity prevalence. A combination of factors could be responsible for this. For one, while this population is often considered to be of retirement age and eligible for Social Security benefits, it is also true that elderly Americans are staying in the workforce longer now than in past decades.[129] This is especially true for low-income elderly households: only 22% of poor families with elderly members receive income from investments, pensions, or retirement accounts, and only 67% of these households receive Social Security benefits.[130] This means that those living near the poverty line must rely more on earned income to cover life expenses. In fact, those over 65 years old make up 3.5% of all minimum wage workers.[131] While there is not a lot of research investigating the impact of minimum wage increases among the elderly population,[132] it is possible that those holding minimum wage jobs may also be more likely to experience employer-driven negative consequences of increased wages such as reduced hours or job loss,[133] and this hypothesis warrants further investigation. It is also true that low-income seniors experience a disproportionate burden of health care costs.[130,134] While many health services for seniors are covered by Medicare – and low-income seniors may also qualify for Medicaid – they may still have to pay out-out-pocket for uncovered services such as long-term care, dental, vision, and hearing aids, and some may not be covered at all if they (or a spouse) did not work in the U.S. and pay Medicare payroll taxes.[135,136] Considering the fact that 13% of minimum wage workers were employed in healthcare or personal care and support service occupations in 2019,[137] the cost of these services is likely to increase when minimum wage increases (due to employers passing on the labor expenses to consumers). Therefore, even for non-working households over the age of 65 who are living on fixed incomes, increased uncovered healthcare costs – as well as other increased costs of living – due to increased minimum wages could shift spending away from food and result in increased food insecurity. We were however surprised that the harmful effects of increased minimum wages reversed when elderly SNAP recipients with marginal food security were considered food secure. Considering the fact that excluding those experiencing marginal food security resulted in no effect of minimum wages on food insecurity prevalence for elderly SNAP households, it seems likely that shifts in net income (either directly due to increased wage or indirectly due to increases in other expenses such as healthcare) are largely impacting marginal food security in this population.

While most results stratified by head of household race and ethnicity revealed beneficial or null effects of minimum wage increases, both Black households (without children) and multiracial households (with and without children) experienced increased food insecurity as minimum wages increased. When the USDA definition of food insecurity is used, Hispanic households (with and without children) and Indigenous households (without children) also experienced increased food insecurity as a result of increased wages. Like most public assistance programs, SNAP recipients face many administrative burdens and challenges when applying for and maintaining enrollment in benefits. While the recertification process to maintain benefits varies significantly from state to state,[119] most SNAP recipients must prove continued eligibility by submitting income documentation and completing a caseworker interview and verification process every six to twelve months. SNAP recertification success is actually low,[120] highlighting the difficulties some families have retaining benefits, even if they are still eligible. Past research has also documented racialized disparities in administrative burdens for safety-net programs more generally,[105,106,138] especially for Black applicants who are more likely to report experiencing discrimination based on their race.[107] It is plausible that Black households (and other traditionally marginalized racial and ethnic households) who experience increases in minimum wage also disproportionately experience a loss of benefits from SNAP and other safety-net programs due to institutionalized racism and other barriers associated with benefit administration. This possibility is also worth further exploration.

Similarly, we found that minimum wage increases either reduced or had no effect on food insecurity for every level of education attainment, except for working aged households without children with some college, for whom increased minimum wages were harmful. Workers with some college (no degree) make up over a quarter of the minimum wage workforce,[137] and the reasons they did not complete their degree are largely financial: those who fail to finish college often do not have financial support from their families and must work while taking classes.[139] This may make them more likely to end up in longstanding precarious employment arrangements, such as part-time or temporary positions. In fact, 73% of “gig” workers have some college,[140] suggesting that this population may have difficulties finding stable employment which may persist without further education. Therefore, even if wages increase, unstable employment and unpredictable monthly income may make it hard for these households to both obtain consistent public benefits (i.e. keep up with recertifications) and to plan for cost-of-living expenses, making them more likely to end up food insecure. When the USDA definition of food insecurity is used and when those experiencing marginal food security are excluded, households with children who possess a high school diploma or equivalent also experienced increased food insecurity when minimum wages increased. It is possible that this population experiences similar working conditions and benefit administration challenges as those with some college credits.

Although minimum wage increases were protective against food insecurity among households with children overall – and specifically for married and single-female-headed families – separated or divorced parents as well as households headed by single males experienced increases in food insecurity prevalence. The relationship between minimum wages and food insecurity among this population may be complicated by child support, or lack thereof. While one-half of families who have a parent living outside the household have a legal or informal child support agreement, the majority of these families do not receive full child support payments.[141] Thus, compared to two-parent households, minimum wage increases may not be enough to overcome resulting decreases in SNAP benefits if these families already have a more challenging time paying for child-related related expenses. In particular, single fathers are less likely than single mothers to receive no child support (38.4 vs 28.7% respectively).[141] Further, single fathers are also less likely to participate in public assistance programs (such as WIC and welfare) compared to single mothers, a trend that may be driven by societal stereotypes about gender and parenting and lack of awareness about eligibility (for example, while WIC is targeted at women by name, single fathers are also eligible).[141–143] So while SNAP benefit reductions due to increased wages may be offset by other safety net programs for single female parents, this may not be true for single male parents. Sensitivity analyses revealed that the effects among single parent households – protective among single female parent households and harmful among single male parent households – disappeared when those experiencing marginal food security were classified as food secure, suggesting that changes in minimum wage may be primarily affecting marginal food security among this population.

Finally, all results were sensitive to the inclusion of survey weights. While most point estimates only shifted a little when no weights were used, almost all confidence intervals for unweighted analyses were extremely wide and crossed the null. We therefore may not be able to rule out the possibility that minimum wages have no effect on food insecurity for SNAP recipients, regardless of household demographics.

This study has some limitations. First, while a large proportion of SNAP recipients are likely to be impacted by minimum wage policies, we were unable to distinguish which specific households are employed in minimum wage jobs and were thus directly impacted by changes in minimum wage. However, nearly a third of all SNAP households and more than half of SNAP households with children have income from earnings,[144] so a reasonable proportion of the study population is likely impacted. Since our exposure was state-level minimum wages, we were also unable to take into account more localized minimum wages (such as at the city or county level),[20] which would supersede the state wage when higher. Second, due to limitations of the Current Population Survey, we were only able to follow households for two consecutive years and were thus unable to examine lagged impacts that may have occurred in the years following a minimum wage increase. It is possible that the addition of more years could diminish any positive effects or exacerbate any negative effects, especially if inflation devalues the benefit of increased wages over time and increases household expenses.[145] Third, since food security for the entire year is measured via the Current Population Survey at a single timepoint (December), temporality may also not be clear; we cannot guarantee that any change in minimum wage occurred prior to a change in household food insecurity status, which could have happened at any point during the calendar year. Fourth, SNAP participation in survey data, including the Current Population Survey, is often significantly underreported, and thus our sample of SNAP participants may not be completely representative.[146,147] Since it is not clear which SNAP recipients may be missing from our sample, this study may be subject to selection bias; if SNAP recipients who are also minimum wage workers are less likely to report SNAP receipt in the Current Population Survey, then this study will have underestimated true effects. Lasty, outcome and covariate measures in this study rely on accurate self-report. As in any survey, this study may be subject to non-response and self-report biases, along with recall errors and resulting misclassification. We used survey weights to account for systematic differences between those who chose to participate in the Current Population Survey and those who did not. Self-report and classification errors seem unlikely to be differential with respect to the exposure (changes in minimum wages).

There are several strengths to note about this study as well. This study is one of the first (that we are aware of) to examine the relationship between state-level minimum wages and food insecurity among SNAP recipients at the national level. Insights from this work are especially valuable, given that SNAP households experience high levels of food insecurity and increases in income directly impact the SNAP benefits a household receives. Our use of the Current Population Survey provided reliable, validated data on food security outcomes that are also nationally representative when population weights are used. Linking households across subsequently years allowed us to identify SNAP households and track their food security status over time as minimum wages changed, regardless of whether they remained on SNAP benefits in the following year. This eliminated the selection bias by SNAP participation that would have been present had another cross-sectional survey been used. Additionally, the scale of the Current Population Survey allowed sufficient sample sizes to uncover important heterogeneity in effect by race and ethnicity, family structure, and educational attainment (when survey weights were used). Lastly, our analytic approach used state and year fixed effects to rigorously control for state-level differences in baseline food insecurity rates and shared secular trends in food insecurity rates over time, as well as several state- and time-varying confounders and safety-net policies to further minimize bias and isolate the effect of interest.

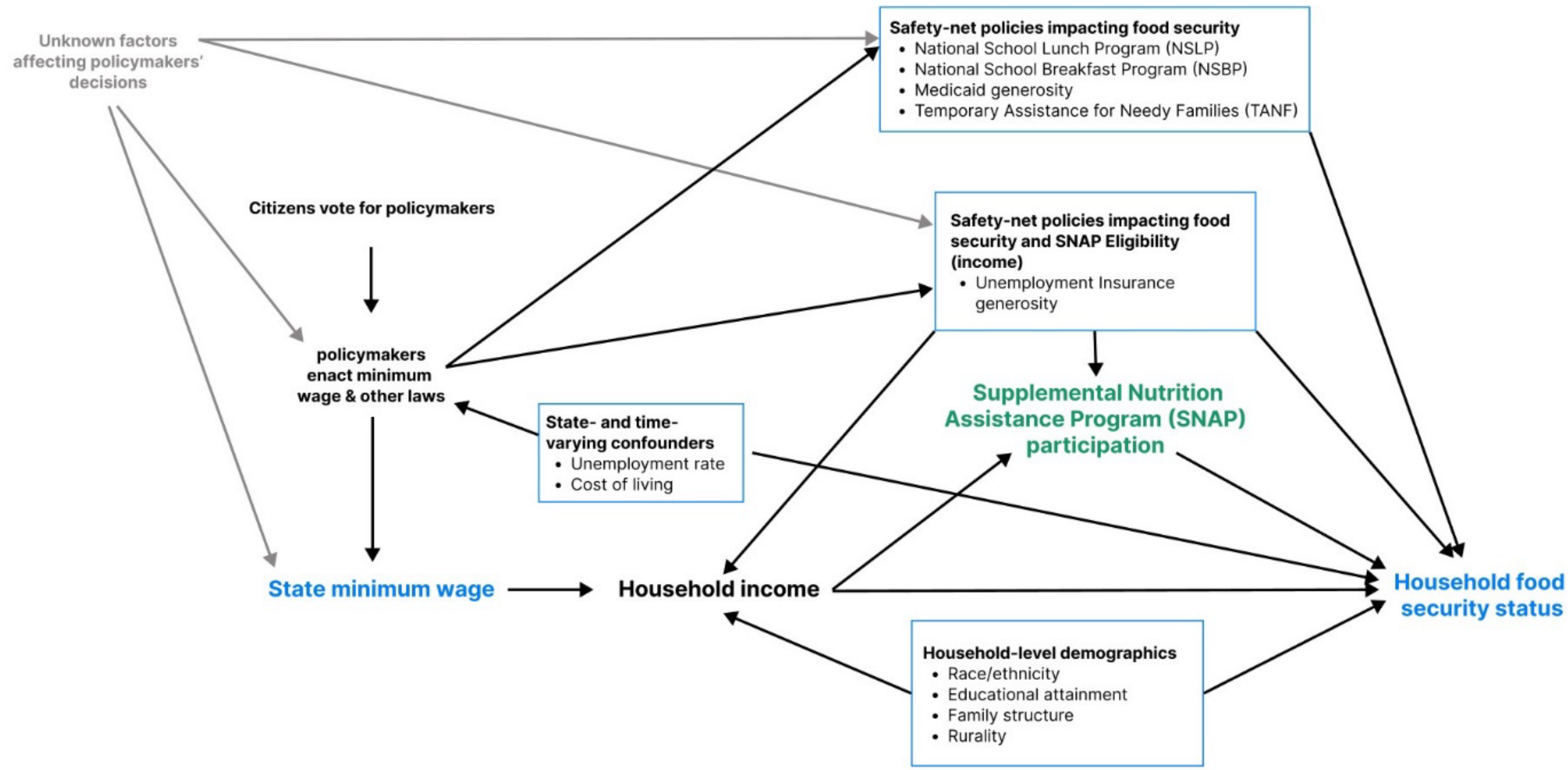
Future work should continue to explore potential mechanisms for heterogeneity in effect, including interactions with other safety-net programs and structural factors such as institutional racism, parental stereotypes, and other administrative burdens preventing access to public benefits. Considering how impactful the classification of those experiencing marginal food security was on results and conclusions, it would also be interesting to examine more granular changes in food insecurity experience by looking at changes in the number of affirmative answers to the food security module questions.

3.5 Conclusions

State-level minimum wage policies hold great potential to provide much needed financial resources to low-income households, including those receiving SNAP benefits. However, potential interactions between minimum wages and safety-net programs are complex: for some demographics increased wages may offset the reduction in SNAP benefits resulting in reduced food insecurity, while for others there is no change in food insecurity status, and for yet others, loss of benefits and recertification challenges may result in increased food insecurity. Future work should continue to explore these complex heterogeneous effects to ensure that all households have sufficient and reliable means for reducing food insecurity. Findings can inform concurrent safety net policy and program changes, target scarce recourses for populations likely to suffer negative impacts, and inform approaches for families transitioning off SNAP.

3.6 Tables and Figures

Figure 3.1. Directed acyclic graph depicting key variables determining household-level food security status among SNAP recipients



Boxed nodes denote variables adjusted for in the analysis including hypothesized confounders (i.e. state-year unemployment rate and cost of living), descendants of confounders (i.e. co-occurring policies such as Medicaid generosity and unemployment insurance generosity), and risk factors for the outcome (i.e. household level demographics such as race and ethnicity and educational attainment). Note that the study population was restricted to those receiving SNAP benefits in their first year of observation.

Figure 3.2. Histogram of effective (real 2019 $) minimum wage changes between consecutive years among SNAP households by whether state had a state-specific policy-mandated minimum wage increase

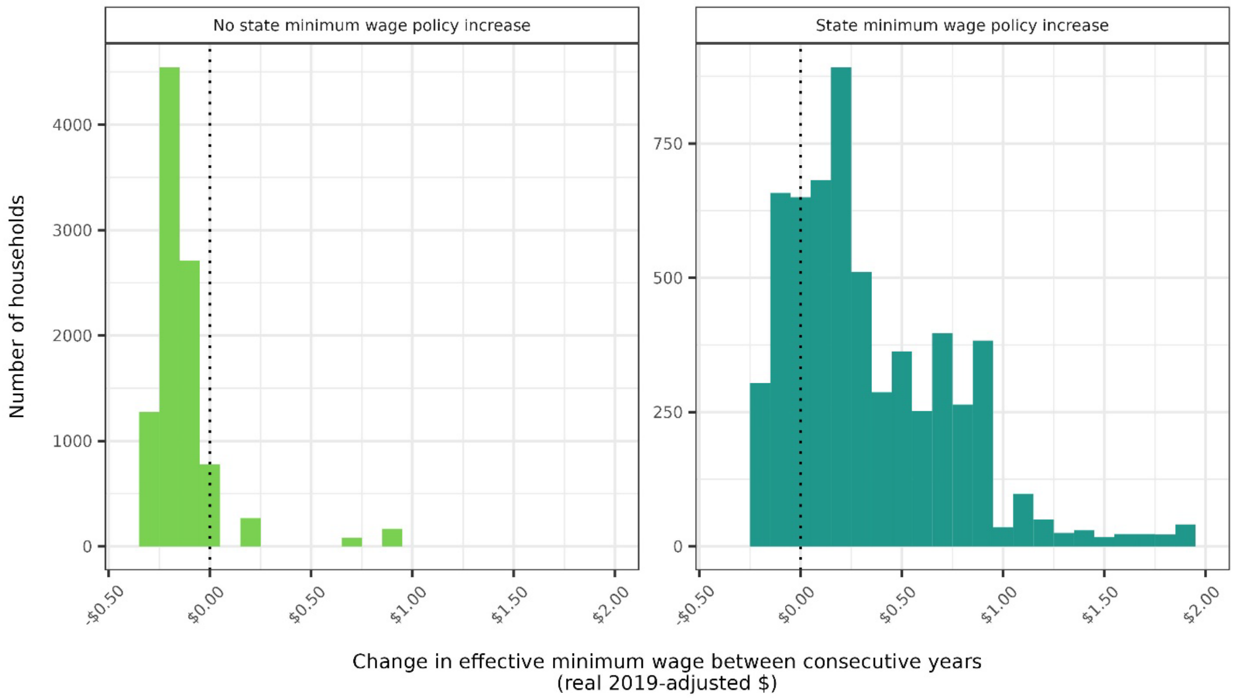


Table 3.1: Household demographics of study sample at baseline (year 1), overall and stratified by whether household lived in a state with a policy-mandated minimum wage change

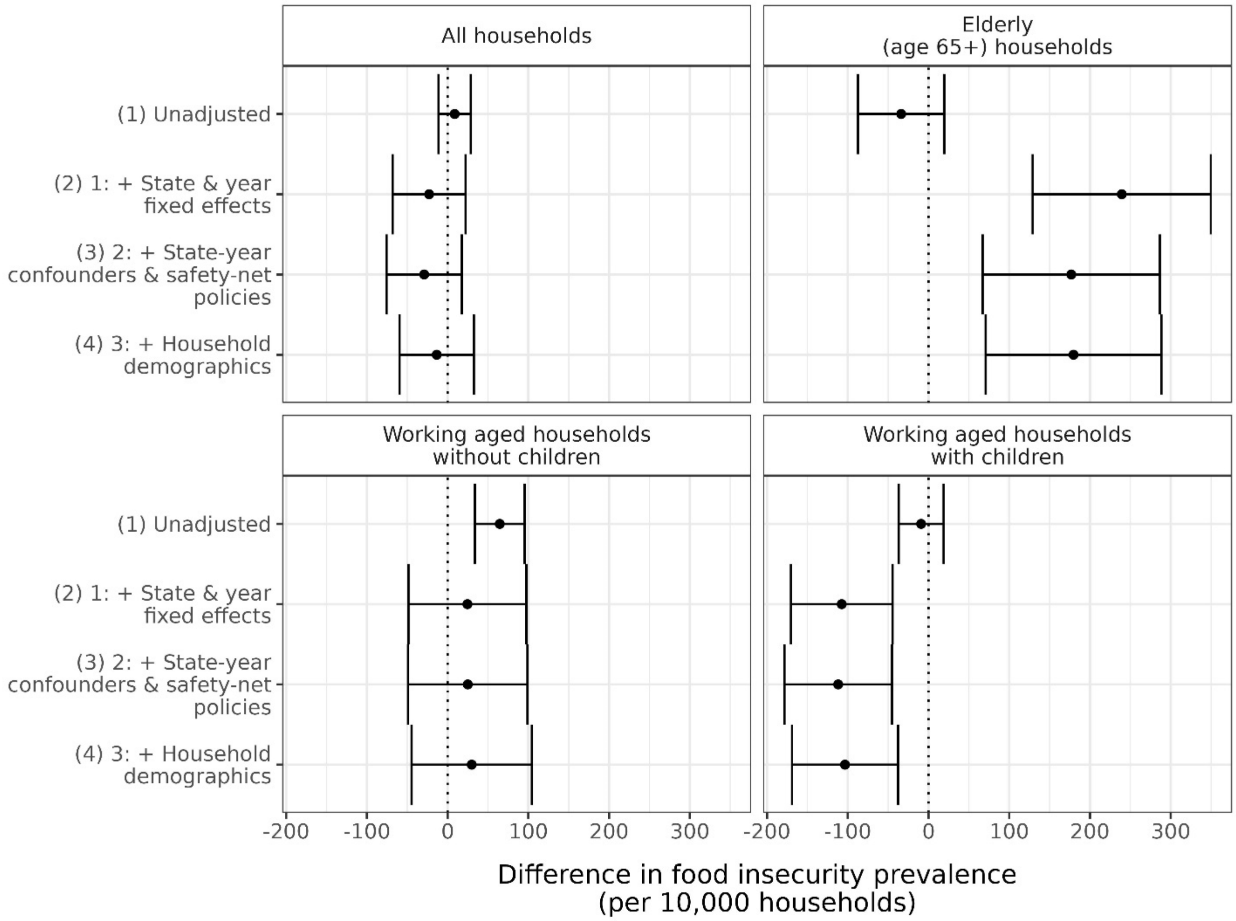
	All households	Households in states without minimum wage policy increase	Households in states with minimum wage policy increase
Number of households	15,845	9,837	6,008
Food security status			
Food Insecure (%)	11,778 (74.3)	7,353 (74.7)	4,425 (73.7)
Young workers, Less than 30 years old (%)	2,479 (19.0)	1,611 (19.8)	8,68 (17.7)
Household/Family structure			
Elderly (age 65+) (%)	2,799 (17.7)	1,683 (17.1)	1,116 (18.6)
Working age* without children (%)	4,963 (31.3)	3,037 (30.9)	1,926 (32.1)
Working age* with children* (%)	8,003 (51.0)	5,117 (52.0)	2,966 (49.4)
Married with children (%)	2,912 (18.4)	1,805 (18.3)	1,107 (18.4)
Separated or divorced parents (%)	2,318 (14.6)	1,492 (15.2)	826 (13.7)
Male single parent** (%)	382 (2.4)	222 (2.3)	160 (2.7)
Female single parent** (%)	2,471 (15.6)	1,598 (16.2)	873 (14.5)
Head of household race/ethnicity			
Non-Hispanic Asian (%)	234 (1.5)	139 (1.4)	95 (1.6)
Non-Hispanic Black (%)	3,564 (22.5)	2,493 (25.3)	1,071 (17.8)
Hispanic (%)	2,570 (16.2)	1,472 (15.0)	1,098 (18.3)
Non-Hispanic Indigenous (%)	421 (2.7)	248 (2.5)	173 (2.9)
Multiracial (%)	334 (2.1)	208 (2.1)	126 (2.1)
Non-Hispanic White (%)	8,722 (55.0)	5,277 (53.6)	3,445 (57.3)
Head of household educational attainment			
Less than high school	4,828 (30.5)	3,118 (31.7)	1,710 (28.5)
High school diploma or equivalent	5,779 (36.5)	3,603 (36.6)	2,176 (36.2)
Some college	2,990 (18.9)	1,799 (18.3)	1,191 (19.8)
At least a college degree	2,248 (14.2)	1,317 (13.4)	931 (15.5)

* *Age 18 to 64*

** *Includes those who have never been married and those who are widowed.*

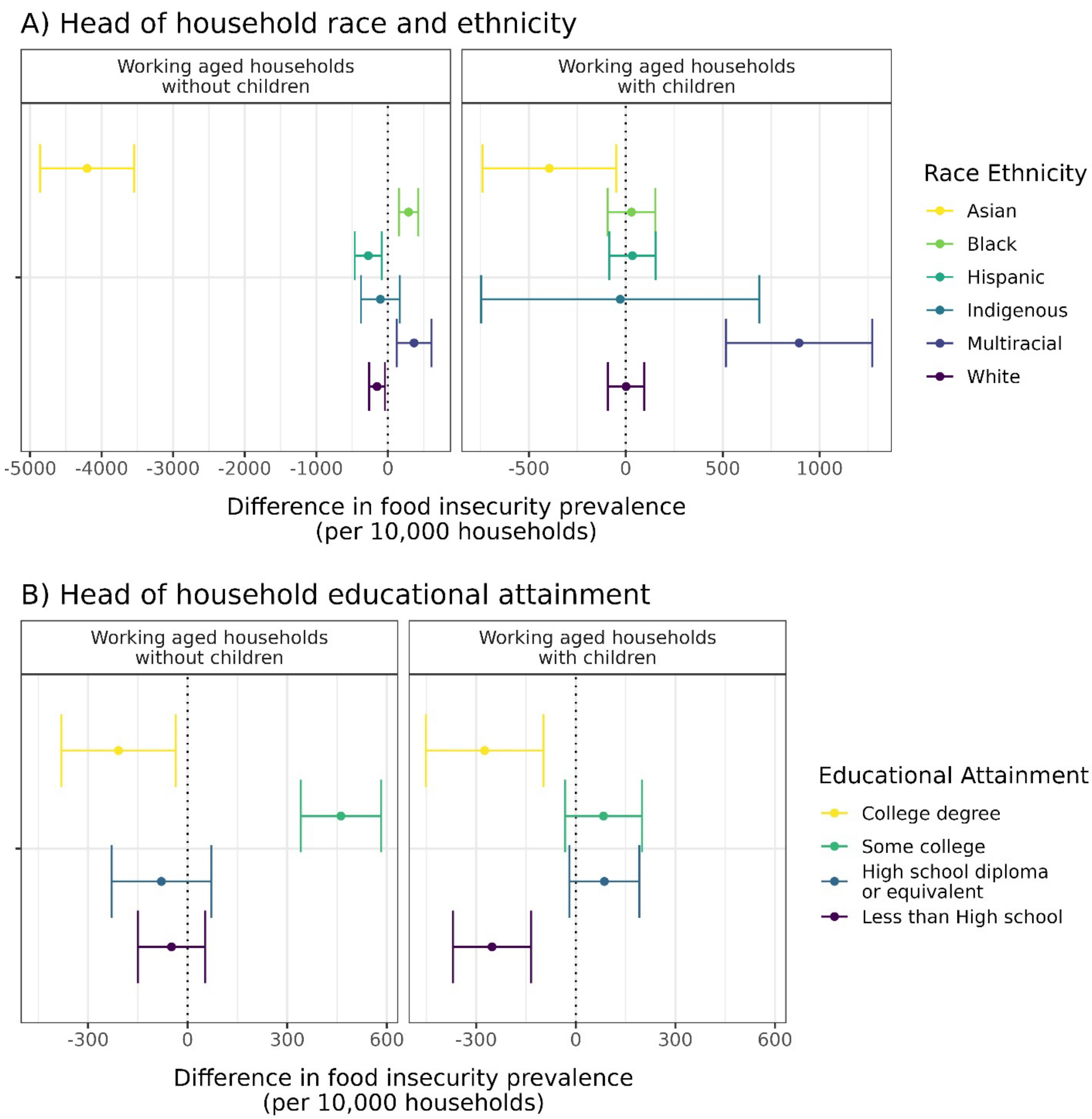
Figure 3.3. Survey-weighted trends in food security status between 2002 and 2019 among SNAP households by sample population, from the Current Population Survey

Figure 3.4. Prevalence differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on food insecurity prevalence among SNAP recipients, separately for all sample populations

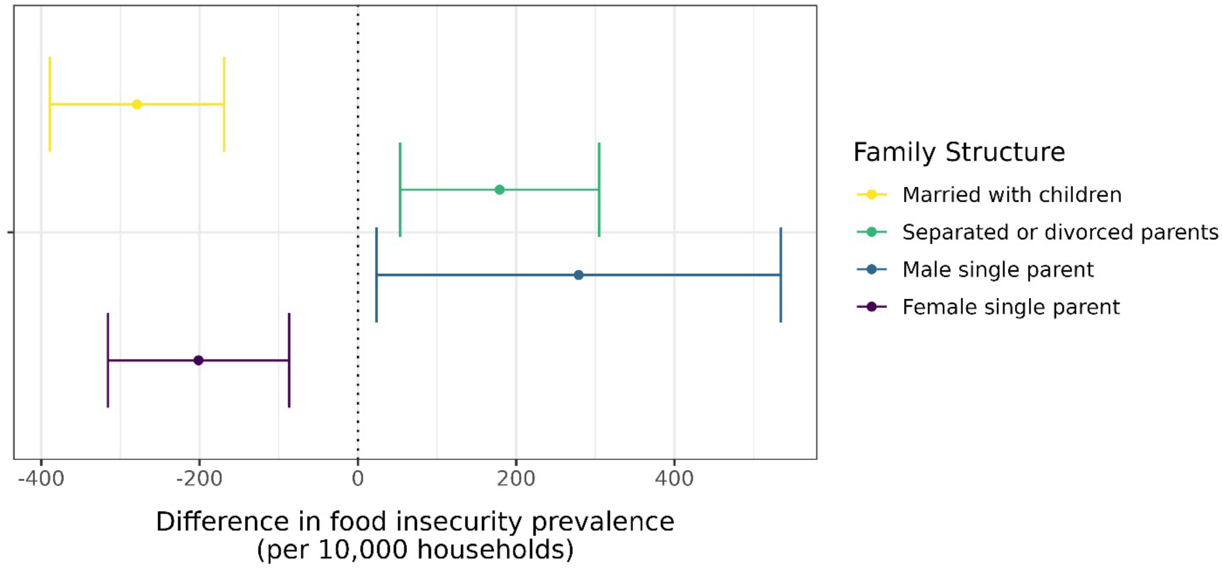


Point estimates and 95% confidence intervals from a linear probability model comparing models with increasing adjustment sets: (1) unadjusted; (2) model 1 plus adjustment for state and year fixed effects; (3) model 2 plus the state- and time-varying confounders and safety-net policies; and (4) model 3 plus household-level demographics. Standard errors were clustered at the household-level and survey weights were included to account for participant selection factors and non-response.

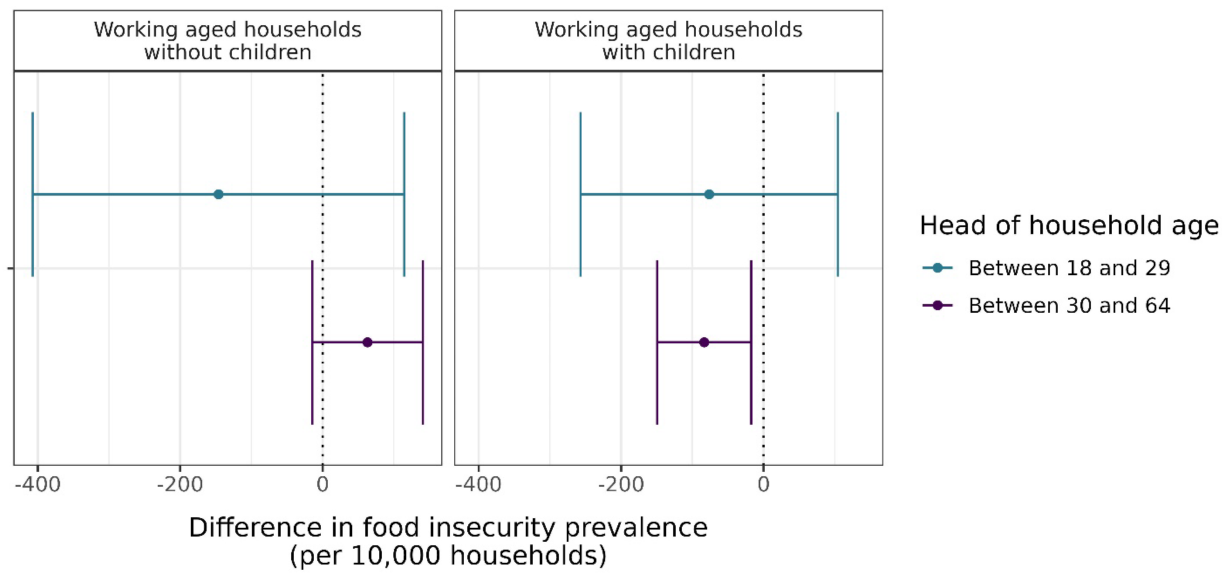
Figure 3.5. Fully adjusted (Model 4) prevalence differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on food insecurity prevalence among working aged SNAP households, stratified by subpopulations of interest



C) Family structure



D) Young vs more experienced workers



In each panel, we compare point estimates and 95% confidence intervals among working aged households with and without children for preferred fully adjusted linear probability model 5 which includes adjustment for state and year fixed effects, state-year confounders and safety-net policies, as well as household-level demographics. Standard errors were clustered at the household-level and survey weights were included to account for participant selection factors and non-response.

3.7 Supplemental Material

Table 3.7.1 Comparison of household characteristics between final analytic sample and those excluded from the full Current Population Survey sample

	Households in December supplement[a]	Households with known food security and SNAP information[b]	Households in final analytic sample[c]
Number of households	599,204	67,826	15,845
Head of household race/ethnicity (%)			
Non-Hispanic Asian	21,169 (3.5)	1,359 (2.0)	234 (1.5)
Non-Hispanic Black	63,768 (10.6)	9,397 (13.9)	3,564 (22.5)
Hispanic	59,999 (10.0)	9,502 (14.0)	2,570 (16.2)
Non-Hispanic Indigenous	7,148 (1.2)	1,238 (1.8)	421 (2.7)
Multiracial	9,070 (1.5)	1,197 (1.8)	334 (2.1)
Non-Hispanic White	438,050 (73.1)	45,133 (66.5)	8,724 (55.1)
Family Structure (%)			
Elderly (age 65+)	131,018 (21.9)	18,139 (26.7)	2,799 (17.7)
Working age* without children	254,463 (42.5)	21,957 (32.4)	4,965 (31.3)
Working age* with children			
Married with children	146,438 (24.4)	15,863 (23.4)	2,912 (18.4)
Separated or divorced parents	36,123 (6.0)	6,124 (9.0)	2,318 (14.6)
Male single parent**	6,768 (1.1)	979 (1.4)	382 (2.4)
Female single parent**	24,394 (4.1)	4,764 (7.0)	2,471 (15.6)
Head of household educational attainment (%)			
Less than High school	70,162 (11.7)	15,410 (22.7)	4,829 (30.5)
High school diploma or equivalent	175,178 (29.2)	24,340 (35.9)	5,779 (36.5)
Some college	112,940 (18.8)	13,275 (19.6)	2,990 (18.9)
College degree	240,924 (40.2)	14,801 (21.8)	2,249 (14.2)
State (%)			
Alabama	8,988 (1.5)	1,211 (1.8)	295 (1.9)
Alaska	7,680 (1.3)	670 (1.0)	149 (0.9)

Table continues on next page

Arizona	8,537 (1.4)	933 (1.4)	202 (1.3)
Arkansas	8,483 (1.4)	1,195 (1.8)	281 (1.8)
California	45,069 (7.5)	4,812 (7.1)	822 (5.2)
Colorado	11,340 (1.9)	1,056 (1.6)	165 (1.0)
Connecticut	10,317 (1.7)	853 (1.3)	199 (1.3)
Delaware	8,044 (1.3)	654 (1.0)	181 (1.1)
District of Columbia	10,122 (1.7)	811 (1.2)	300 (1.9)
Florida	26,054 (4.3)	2,598 (3.8)	598 (3.8)
Georgia	12,456 (2.1)	1,500 (2.2)	391 (2.5)
Hawaii	7,655 (1.3)	646 (1.0)	170 (1.1)
Idaho	7,622 (1.3)	1,096 (1.6)	196 (1.2)
Illinois	17,913 (3.0)	1,768 (2.6)	391 (2.5)
Indiana	9,944 (1.7)	1,141 (1.7)	269 (1.7)
Iowa	10,000 (1.7)	1,227 (1.8)	257 (1.6)
Kansas	8,900 (1.5)	1,205 (1.8)	237 (1.5)
Kentucky	8,599 (1.4)	1,217 (1.8)	319 (2.0)
Louisiana	8,658 (1.4)	1,147 (1.7)	348 (2.2)
Maine	9,414 (1.6)	1,545 (2.3)	424 (2.7)
Maryland	11,075 (1.8)	923 (1.4)	199 (1.3)
Massachusetts	10,279 (1.7)	877 (1.3)	235 (1.5)
Michigan	14,335 (2.4)	1,621 (2.4)	454 (2.9)
Minnesota	11,968 (2.0)	1,254 (1.8)	242 (1.5)
Mississippi	7,692 (1.3)	1,310 (1.9)	377 (2.4)
Missouri	9,785 (1.6)	1,222 (1.8)	305 (1.9)
Montana	8,316 (1.4)	1,169 (1.7)	247 (1.6)
Nebraska	8,988 (1.5)	1,038 (1.5)	161 (1.0)
Nevada	9,239 (1.5)	868 (1.3)	158 (1.0)
New Hampshire	10,633 (1.8)	1,057 (1.6)	178 (1.1)
New Jersey	11,723 (2.0)	853 (1.3)	146 (0.9)
New Mexico	7,359 (1.2)	986 (1.5)	272 (1.7)
New York	25,205 (4.2)	2,456 (3.6)	753 (4.8)
North Carolina	12,956 (2.2)	1,661 (2.4)	392 (2.5)
North Dakota	8,655 (1.4)	895 (1.3)	191 (1.2)
Ohio	16,638 (2.8)	2,207 (3.3)	543 (3.4)
Oklahoma	8,077 (1.3)	1070 (1.6)	235 (1.5)
Oregon	8,961 (1.5)	1040 (1.5)	343 (2.2)
Pennsylvania	18,252 (3.0)	2,133 (3.1)	450 (2.8)
Rhode Island	8,898 (1.5)	1,073 (1.6)	291 (1.8)
South Carolina	8,578 (1.4)	1,238 (1.8)	316 (2.0)
South Dakota	8,773 (1.5)	1,173 (1.7)	232 (1.5)

Table continues on next page

Tennessee	9,464 (1.6)	1,215 (1.8)	305 (1.9)
Texas	30,258 (5.0)	3,660 (5.4)	917 (5.8)
Utah	7,198 (1.2)	796 (1.2)	125 (0.8)
Vermont	8,785 (1.5)	1,038 (1.5)	287 (1.8)
Virginia	11,780 (2.0)	922 (1.4)	173 (1.1)
Washington	10,703 (1.8)	1,148 (1.7)	296 (1.9)
West Virginia	9,406 (1.6)	1,369 (2.0)	398 (2.5)
Wisconsin	10,905 (1.8)	1,273 (1.9)	267 (1.7)
Wyoming	8,525 (1.4)	996 (1.5)	165 (1.0)

[a] *Unique households who participated in the December supplement of the Current Population Survey between 2002 and 2019.*

[b] *Households who participated in the December supplement of the Current Population Survey between 2002 and 2019 with two consecutive years of data including known food security status and SNAP participation information for both years.*

[c] *Households who participated in the December supplement of the Current Population Survey between 2002 and 2019 with two consecutive years of data including known food security status and SNAP participation information for both years, further restricted to those who had received SNAP benefits during their first interview year (regardless of whether they received benefits in their second year) and excluding 8 households living in group quarters.*

[*] *Age 18 to 64*

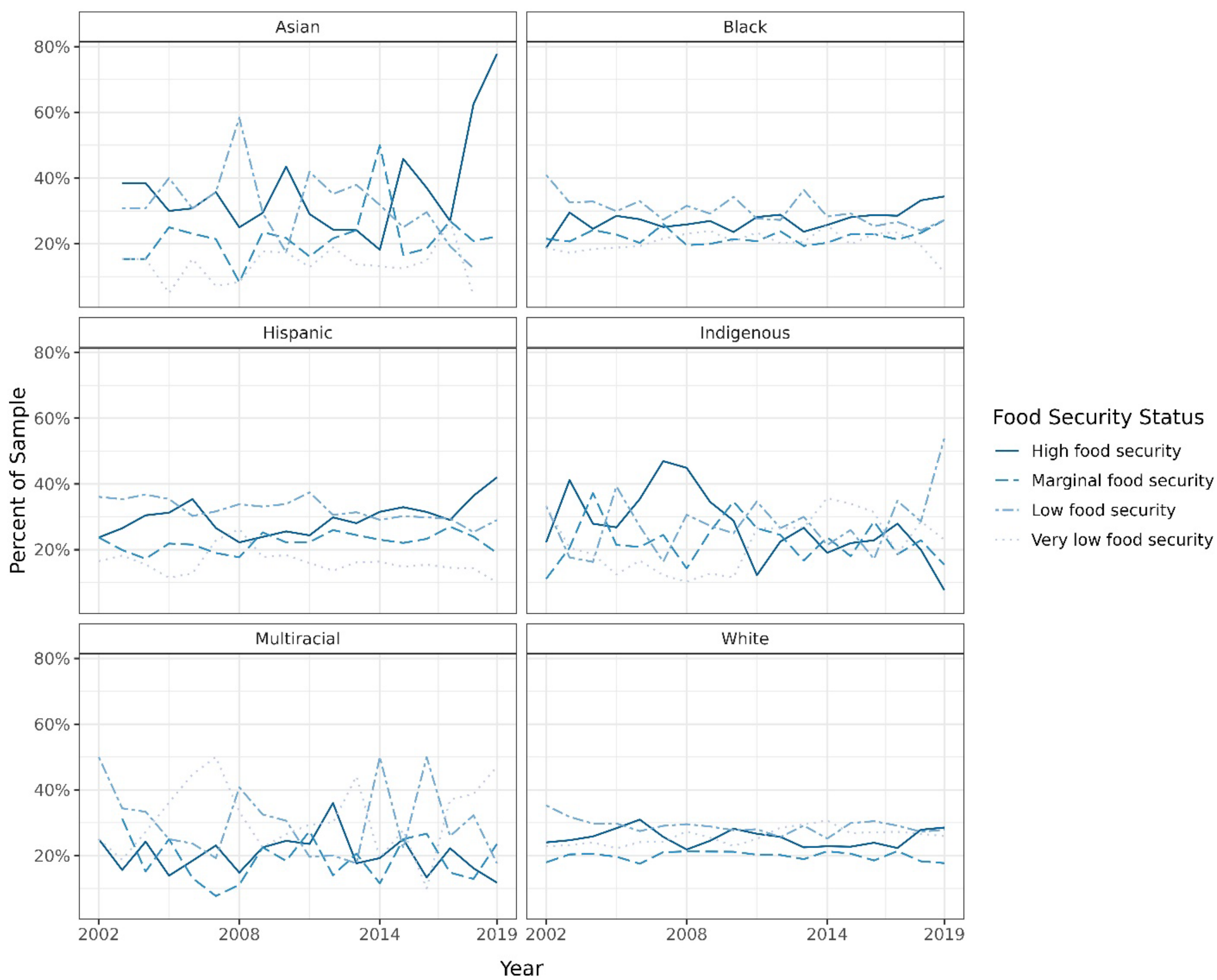
[**] *Includes those who have never been married and those who are widowed.*

3.7.2 Post hoc analyses of the subpopulation of working-aged households with an Asian head-of-household

Given implausibly large effect estimates for the subpopulation of households with a working-aged (between 18-64 years old) Asian head-of-household (hereafter “Asian households” for brevity) we sought to investigate – and potentially mitigate – data anomalies that may be driving these results. Note that this subpopulation is by the far the smallest in our sample, consisting of only 53 households without children and 129 households with children.

First, we first examined food security status trends, stratified by race and ethnicity (Supplemental Figure 3.1).

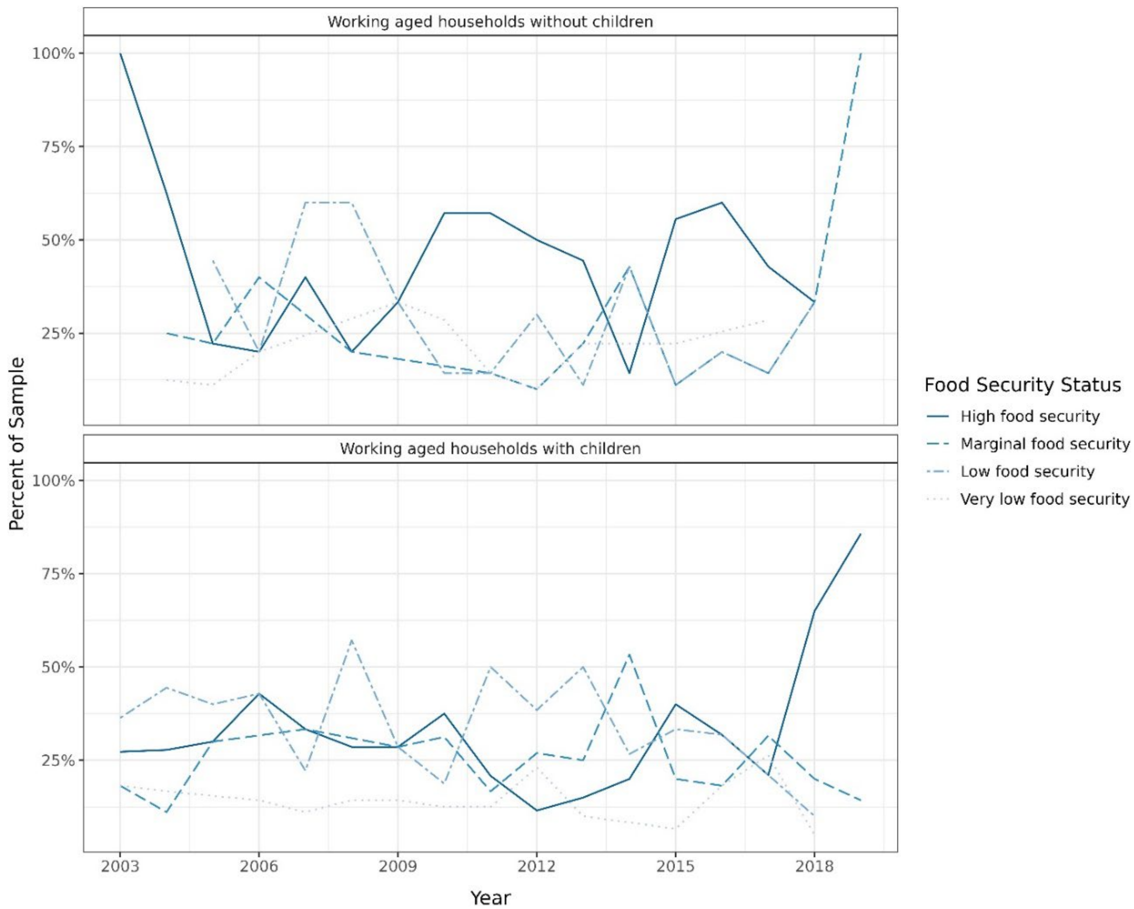
Supplemental Figure 3.1 Survey-weighted trends in food security status between 2002 and 2019 among working aged SNAP households by race-ethnicity, from the Current Population Survey



It was immediately clear that Asian households experienced an unusual spike in high food security status in the years of 2018 and 2019. We also noticed that there are no (working-aged) Asian households in our sample in the year 2002. While trends among Indigenous and Multiracial households are not smooth, no other racial-ethnic subpopulation appears to be experiencing similar spikes or missing data.

We then looked at trends among Asian households with and without children and noticed a similar outlier where 100% of households without children in the year 2003 had high food security (Supplemental Figure 3.2).

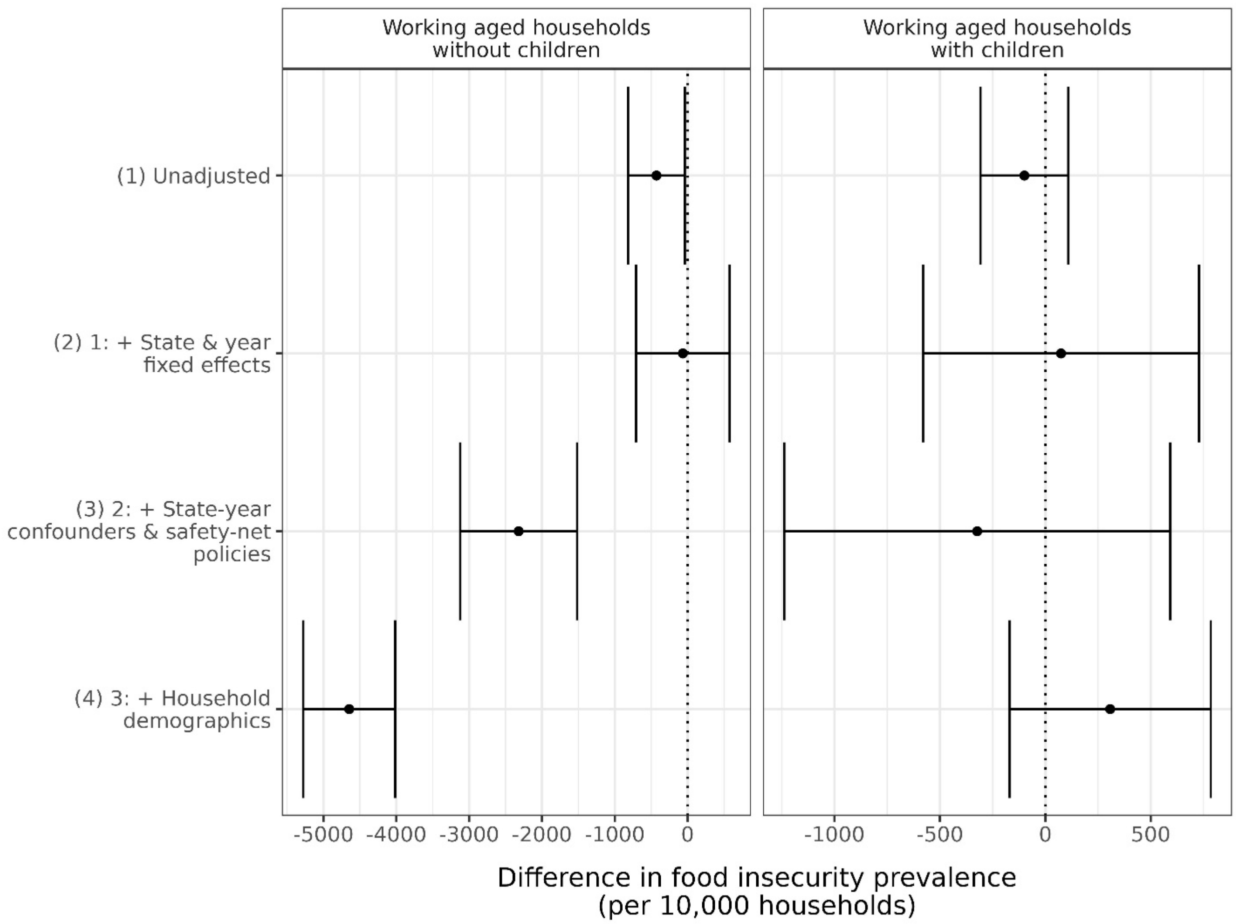
Supplemental Figure 3.2. Trends in food security status between 2002 and 2019 among working aged Asian SNAP households by presence of children



Next, we re-ran the main model among Asian households only, removing the years with missing data and potential outlier years (2002, 2003, 2018, and 2019) to determine how effect estimates were impacted.

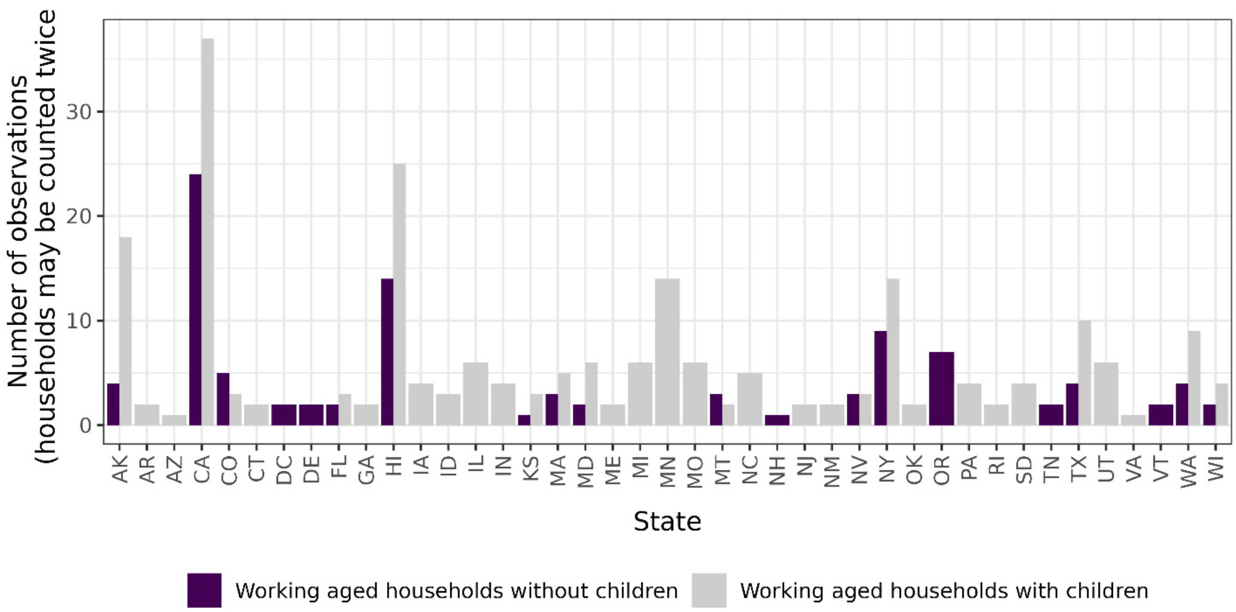
Removal of the years 2002, 2003, 2018 and 2019 resulted in null effect estimates among Asian households with children [PD = 307, 95%CI = (-170, 785) compared to the original estimate of PD = -394 and original 95%CI = (-739, -50)], while there was little change in the effect estimate among Asian households without children [PD = 4,647, 95%CI = (-5,278, -4,015) compared to the original estimate of PD = -4,201 and original 95%CI = (-4,857, -3,546)] (Supplemental Figure 3.3).

Supplemental Figure 3.3. Prevalence differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on food insecurity prevalence among Asian SNAP recipients between 2004 and 2017.



We therefore examined whether state representation in our data set could be responsible for the large effect estimates and determined that Asian households without children in this restricted sample reside in only 20 states (Supplemental Figure 3.4). A full quarter of these households live in California, another 14.6% live in Hawaii, and a further 9% live in New York. Note that since we removed four years of observations, households may no longer have 2 years of data in this restricted dataset, so these statistics represent single observations (and some households may be double counted). Residents of these states may not be representative of the U.S. overall – for example, these states have some of the highest living costs[148] but also some of the most generous social safety net policies.[149]

Supplemental Figure 3.4. Number of working-aged Asian SNAP household observations by state and presence of children



While we were unable to conclude whether data anomalies and outliers due to small sample sizes in this population are responsible for the extremely large effect estimates among working aged Asian SNAP households, it is very likely that this result does not generalize to all Asian SNAP households in the U.S. Further analysis of this group with more complete data is warranted.

3.7.3 Supplemental Figures and Tables

Supplemental Table 3.1. Prevalence differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on food insecurity prevalence by sample population

Model	**Difference in food insecurity prevalence per 10,000 households (95% confidence Interval)**			
	All Households ***(n = 15,845)***	**Elderly (age 65+) households** ***(n = 2,799)***	**Working aged households without children** ***(n = 4,963)***	**Working aged households with children** ***(n = 8,083)***
(1) Unadjusted	9 (-11, 29)	-34 (-87, 20)	65 (34, 95)	-9 (-37, 19)
(2) Model 1 + adjustment for state and year fixed effects	-23 (-68, 22)	239 (129, 350)	25 (-49, 98)	-107 (-170, -45)
(3) Model 2 + adjustment for state and year fixed effects + state-year confounders and safety-net policies	-29 (-76, 18)	177 (67, 287)	25 (-49, 99)	-112 (-178, -45)
(4) Model 3 + adjustment for state and year fixed effects + state-year confounders and safety-net policies + household-level demographics	-13 (-60, 33)	180 (71, 288)	30 (-45, 104)	-103 (-169, -38)

Supplemental Table 3.2. Fully adjusted (Model 4) prevalence differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on food insecurity prevalence, by sample population and stratified by subpopulations of interest

Subpopulation	Sample size: Working aged households without children (with children)	Difference in food insecurity prevalence per 10,000 households (95% confidence Interval)	
		Working aged households without children	Working aged households with children
Head of household race/ethnicity			
Non-Hispanic Asian	53 (129)	-4,201 (-4,857, -3,546)	-394 (-739, -50)
Non-Hispanic Black	1,100 (1,835)	289 (155, 423)	29 (-94, 152)
Hispanic	472 (1,788)	-274 (-463, -86)	34 (-85, 153)
Non-Hispanic Indigenous	128 (242)	-105 (-376, 165)	-29 (-747, 689)
Multiracial	137 (152)	365 (123, 608)	894 (516, 1,271)
Non-Hispanic White	3,073 (3,937)	-153 (-263, -42)	2 (-92, 95)
Family structure (working aged households with children only)			
Married with children	(2,912)	-	-279 (-389, -169)
Separated or divorced parents	(2,318)	-	179 (53, 305)
Male single parent*	(382)	-	279 (24, 534)
Female single parent*	(2,471)	-	-201 (-316, -87)

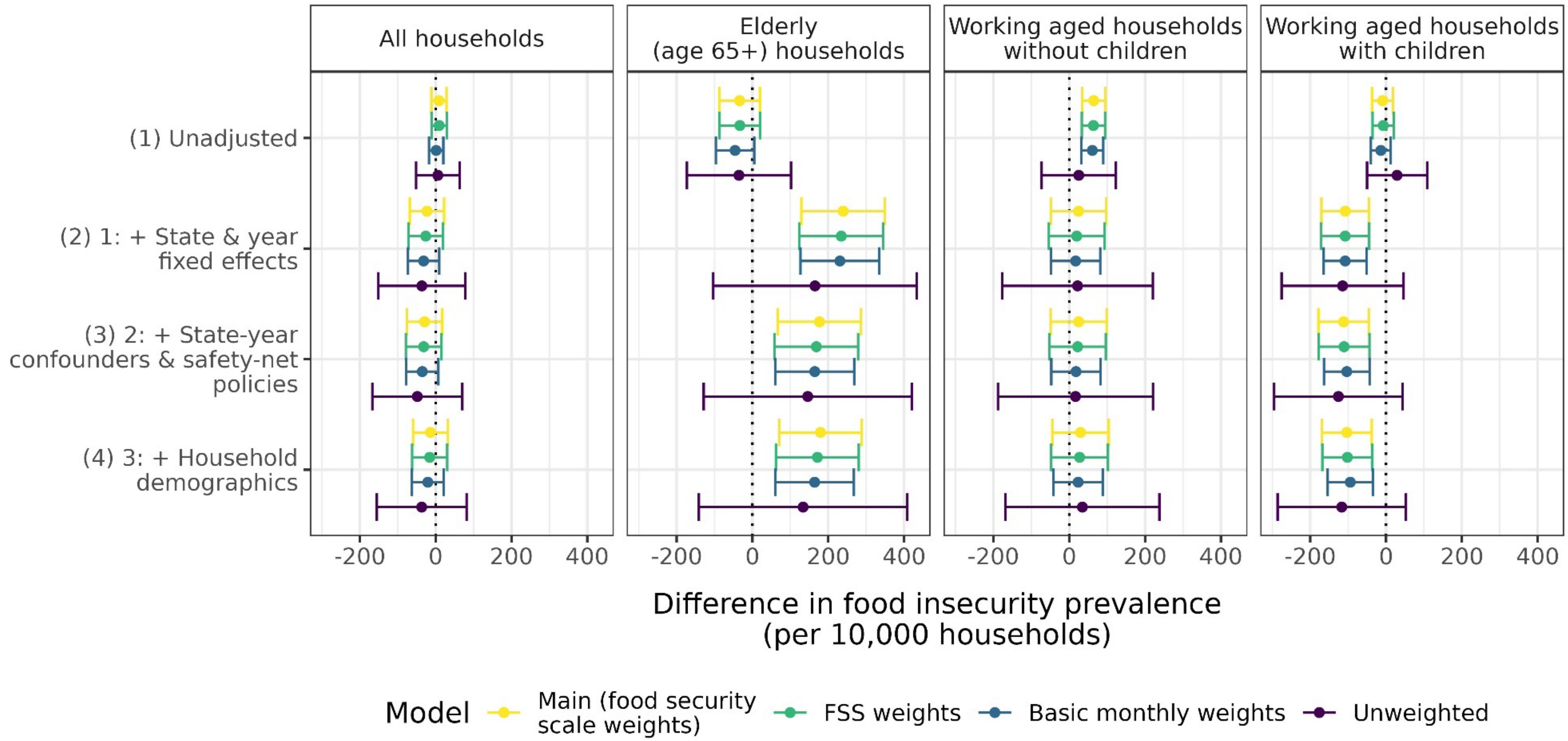
Table continues on next page

Subpopulation	Sample size: Working aged Households without children (with children)	Difference in food insecurity prevalence per 10,000 households (95% confidence Interval)	
		Working aged households without children	Working aged Households with children
Head of household educational attainment			
Less than high school	1,413 (2,141)	-49 (-150, 52)	-252 (-370, -135)
High school diploma or equivalent	1,860 (3,042)	-79 (-229, 71)	86 (-19, 191)
Some college	954 (1,706)	462 (341, 583)	84 (-32, 200)
At least a college degree	736 (1,194)	-208 (-381, -36)	-274 (-451, -98)
Young vs more experienced workers			
Ages 18 to 29	524 (1,955)	-146 (-407, 115)	-76 (-257, 104)
Ages 30 to 64	4,439 (6,128)	63 (-15, 141)	-83 (-149, -17)

Preferred fully adjusted linear probability model 4 includes adjustment for state and year fixed effects, state-year confounders and safety-net policies, as well as household-level demographics. Standard errors were clustered at the household-level and survey weights were included to account for participant selection factors and non-response.

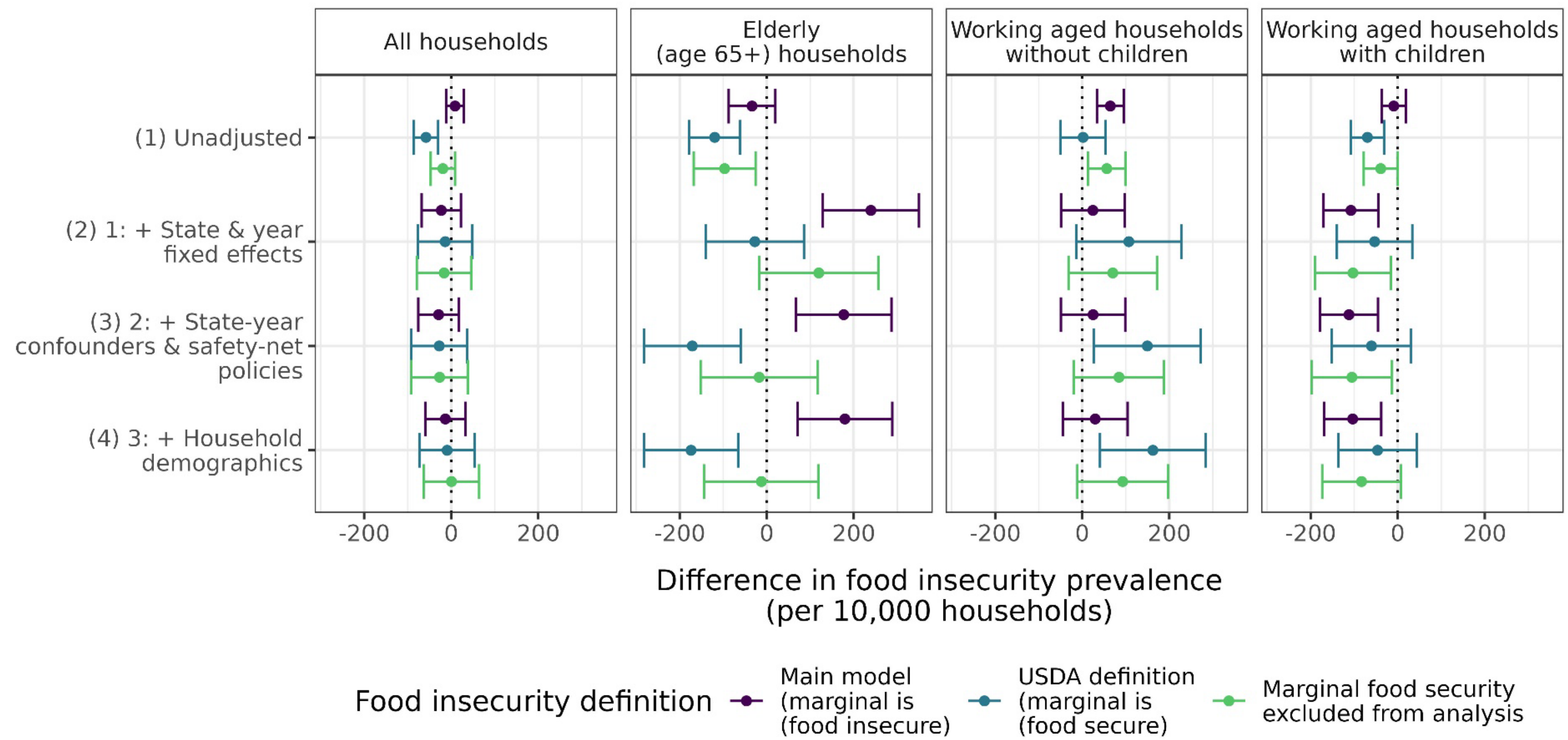
[*] *Includes those who have never been married and those who are widowed.*

Supplemental Figure 3.5. Prevalence differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on food insecurity prevalence, comparing use of survey weights



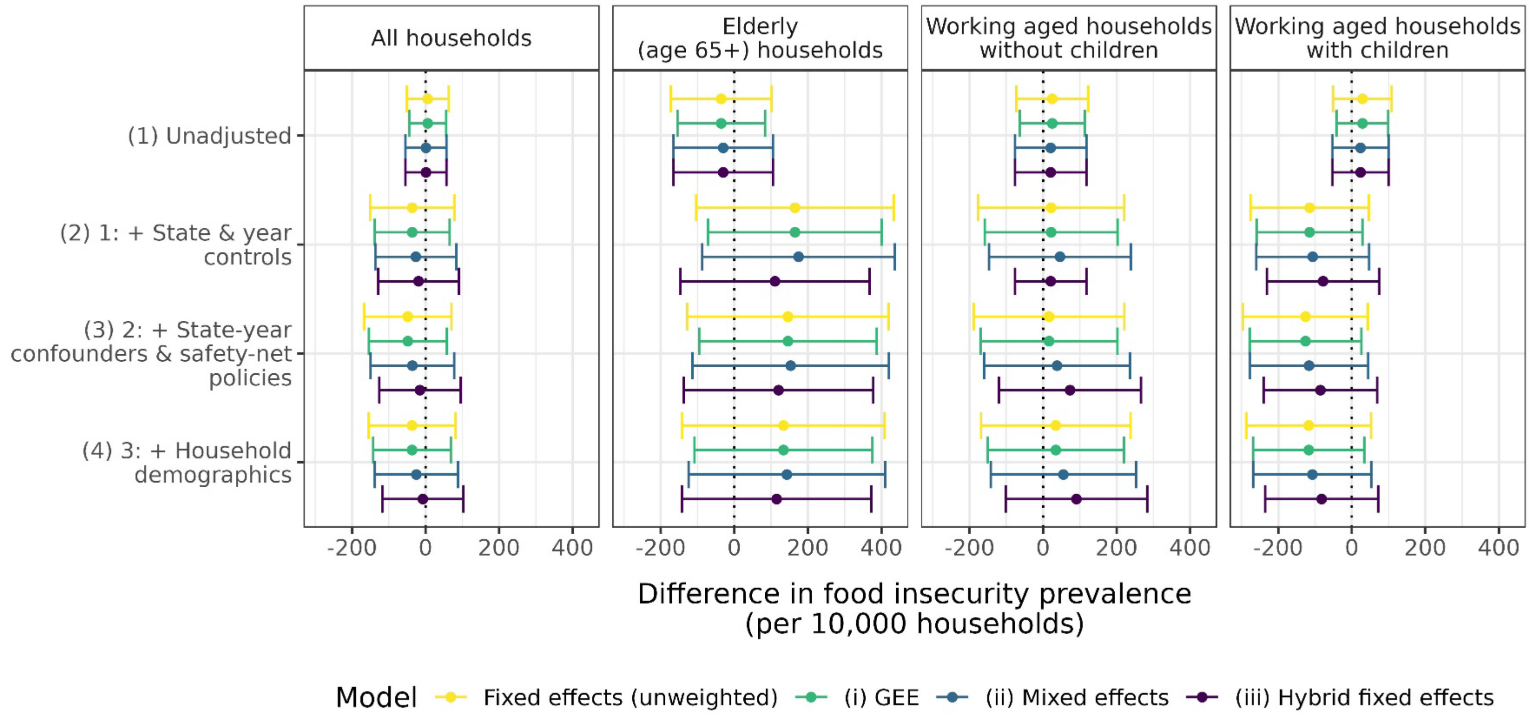
Point estimates and 95% confidence intervals from a linear probability model comparing models with increasing adjustment sets: (1) unadjusted; (2) model 1 plus adjustment for state and year fixed effects; (3) model 2 plus the state- and time-varying confounders and safety-net policies; and (4) model 3 plus household-level demographics. Standard errors were clustered at the household-level. The main model used the food security scale weights ("FSHWTSCALE"), the FSS weights model used "FSSUPPWTH" weights, and the basic monthly weights model used "HWTFINL" weights to account for participant selection factors and non-response.

Supplemental Figure 3.6. Prevalence differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on food insecurity prevalence, by food insecurity definition



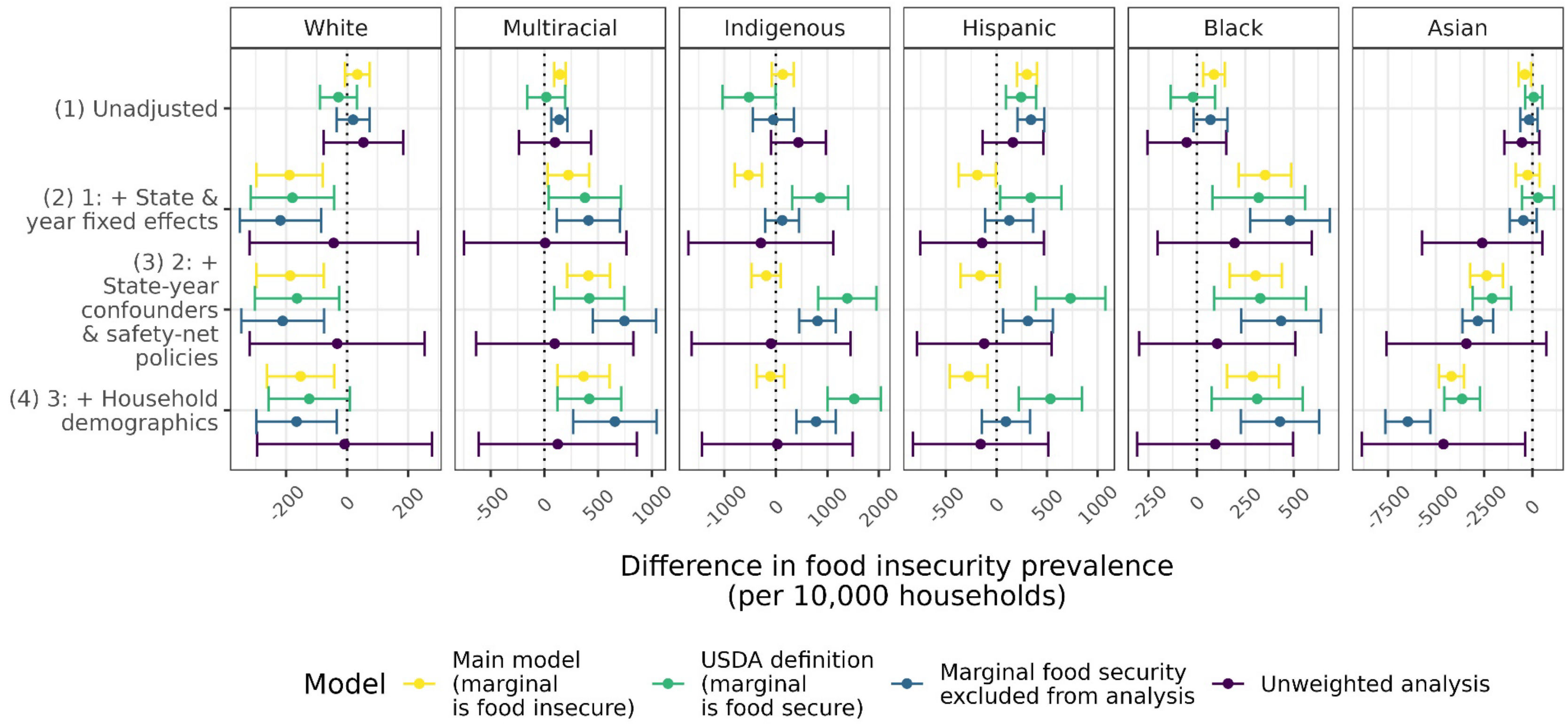
Point estimates and 95% confidence intervals from a linear probability model comparing models with increasing adjustment sets: (1) unadjusted; (2) model 1 plus adjustment for state and year fixed effects; (3) model 2 plus the state- and time-varying confounders and safety-net policies; and (4) model 3 plus household-level demographics. Standard errors were clustered at the household-level and survey weights were included to account for participant selection factors and non-response. Main model classifies households experiencing very low, low, or marginal food security as food insecure and those with high food security as food secure, while the U.S. Department of Agriculture (USDA) classifies households experiencing very low or low food security as food insecure and those with marginal or high food security as food secure. Final model comparison excludes those with marginal food security from the analysis.

Supplemental Figure 3.7. Prevalence differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on food insecurity prevalence, by (unweighted) model specification



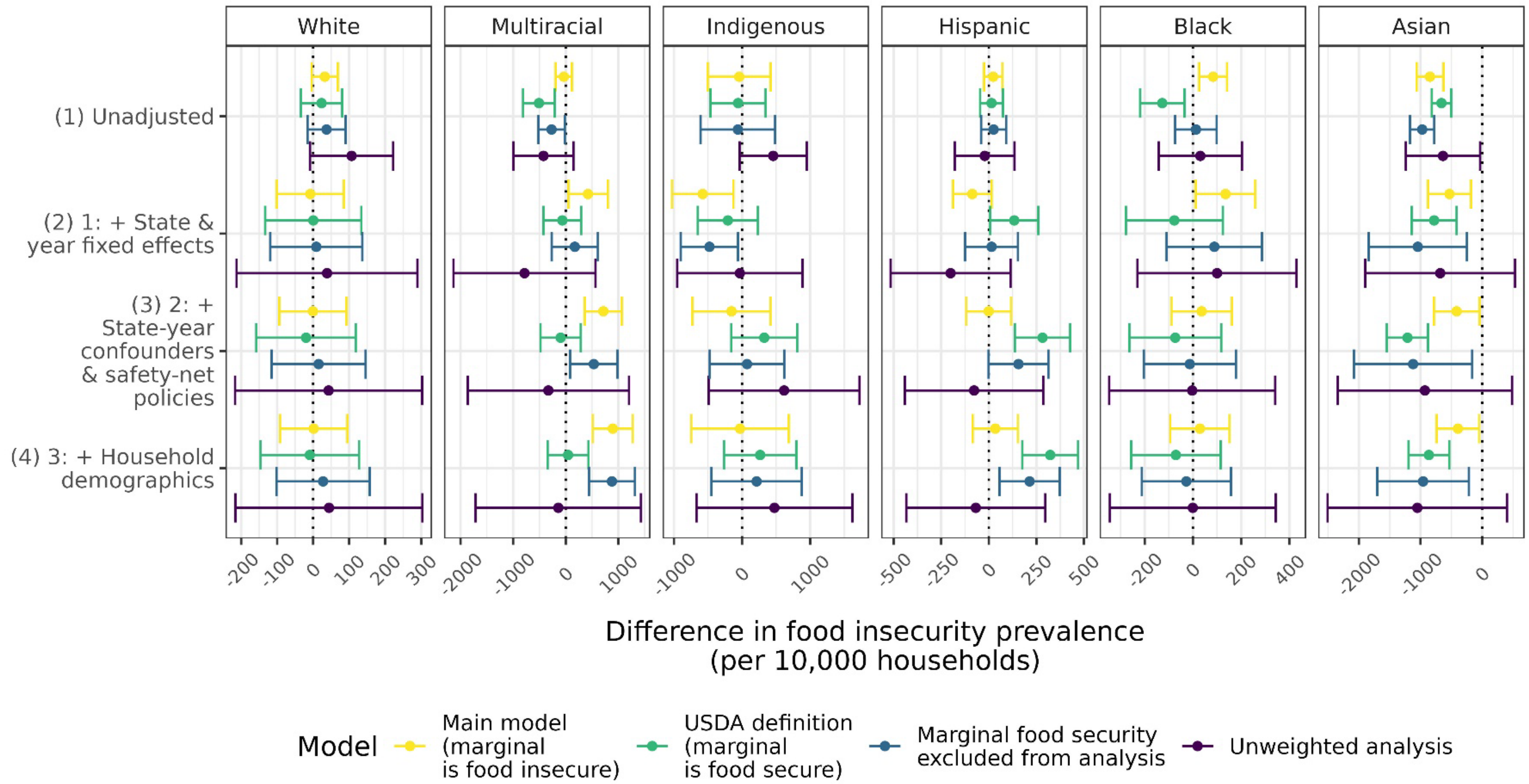
Point estimates and 95% confidence intervals comparing unweighted models with increasing adjustment sets: (1) unadjusted; (2) model 1 plus adjustment for state and year controls; (3) model 2 plus the state- and time-varying confounders and safety-net policies; and (4) model 3 plus household-level demographics. Model (i) used a generalized estimating equation (GEE) with an exchangeable correlation structure, model (ii) used a linear mixed effects model with household-specific random intercepts, and model (iii) used a linear hybrid fixed effects model with household-specific random intercepts. All models were compared to an unweighted version of the main linear probability (fixed effects) model whose standard errors were clustered at the household-level. All models utilized state and year fixed effects for the state and year controls except for the hybrid model which utilized state-specific minimum wage means and year-specific minimum wage means.

Supplemental Figure 3.8. Sensitivity analysis for race and ethnicity subpopulation results, comparing main survey weighted model with unweighted model and with model using the USDA definition of food insecurity among working aged households without children



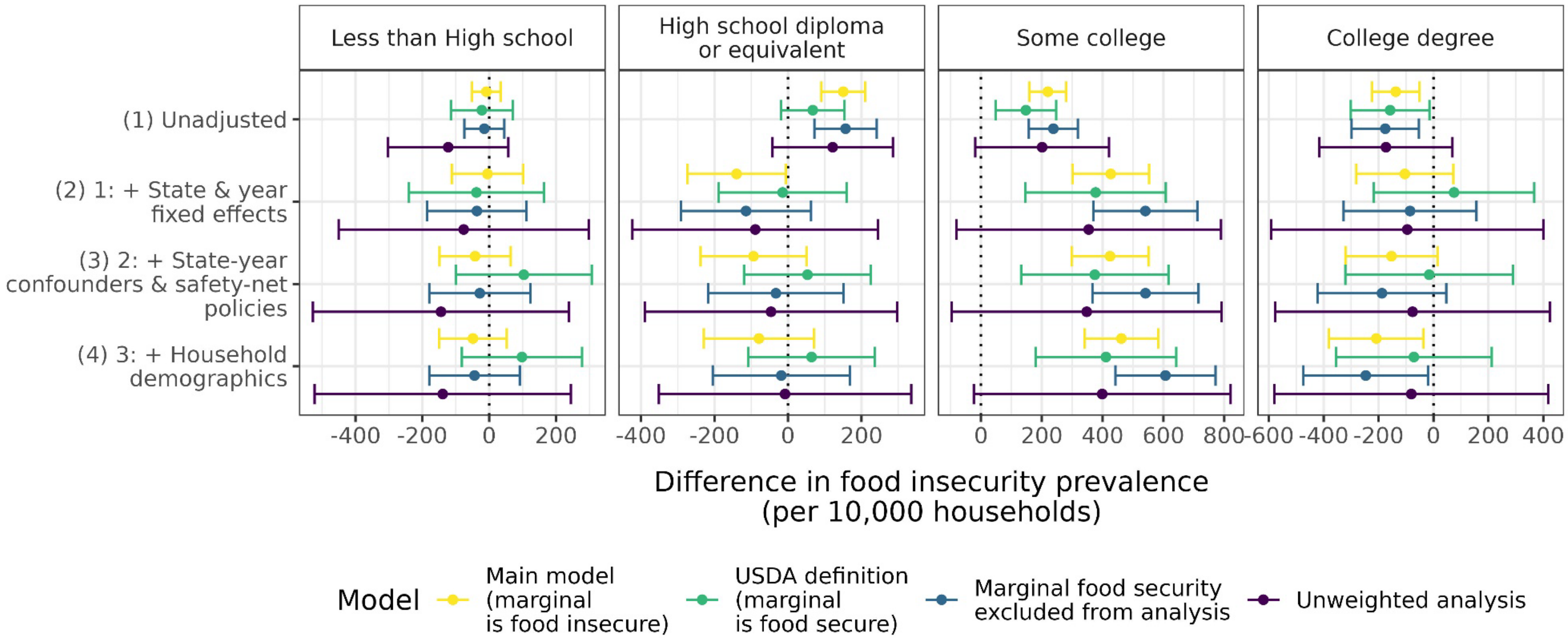
Point estimates and 95% confidence intervals from a linear probability model comparing models with increasing adjustment sets: (1) unadjusted; (2) model 1 plus adjustment for state and year fixed effects; (3) model 2 plus the state- and time-varying confounders and safety-net policies; and (4) model 3 plus household-level demographics. Standard errors were clustered at the household-level. The main model used the food security scale weights, the unweighted model used no weights, and the alternative definition of food insecurity model used the food security scale weights and classified those with marginal food security status as being food secure (as opposed to food insecure as in the main and unweighted models).

Supplemental Figure 3.9. Sensitivity analysis for race and ethnicity subpopulation results, comparing main survey weighted model with unweighted model and with model using the USDA definition of food insecurity among working aged households with children



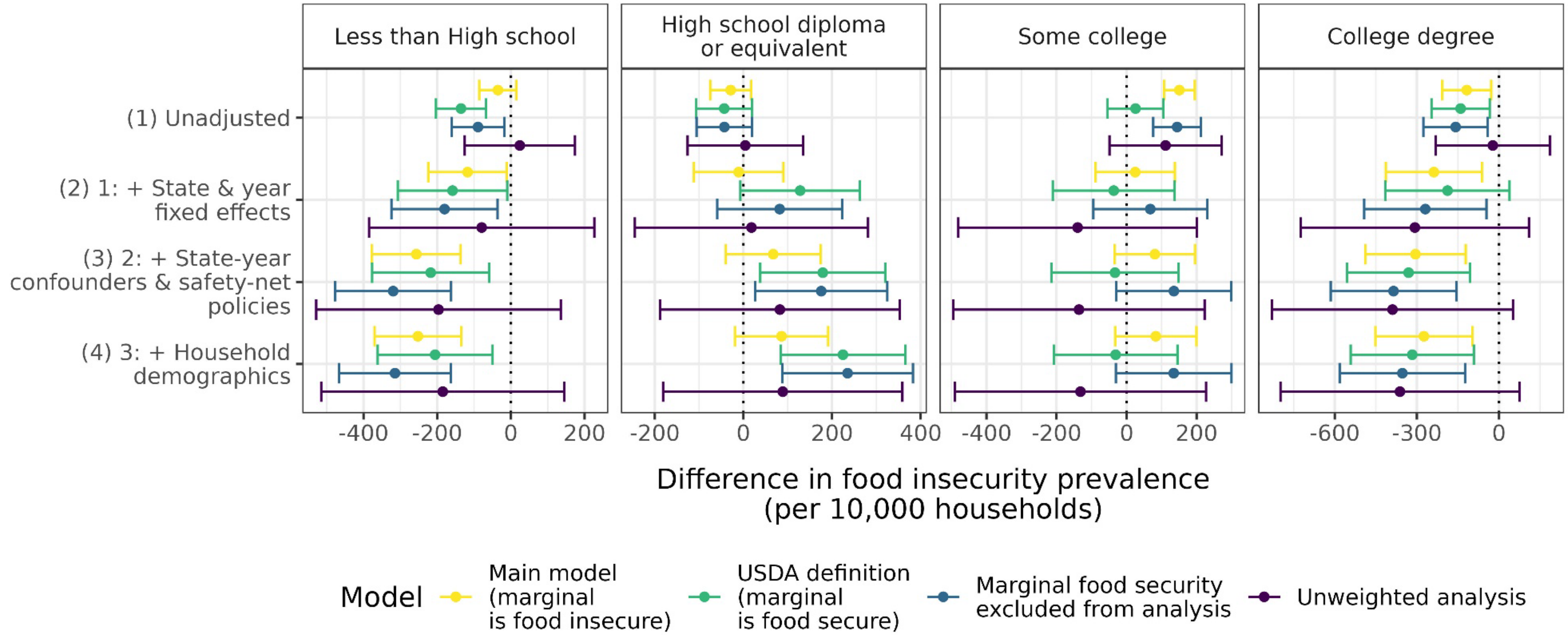
Point estimates and 95% confidence intervals from a linear probability model comparing models with increasing adjustment sets: (1) unadjusted; (2) model 1 plus adjustment for state and year fixed effects; (3) model 2 plus the state- and time-varying confounders and safety-net policies; and (4) model 3 plus household-level demographics. Standard errors were clustered at the household-level. The main model used the food security scale weights, the unweighted model used no weights, and the alternative definition of food insecurity model used the food security scale weights and classified those with marginal food security status as being food secure (as opposed to food insecure as in the main and unweighted models).

Supplemental Figure 3.10. Sensitivity analysis for educational attainment subpopulation results, comparing main survey weighted model with unweighted model and with model using the USDA definition of food insecurity among working aged households without children



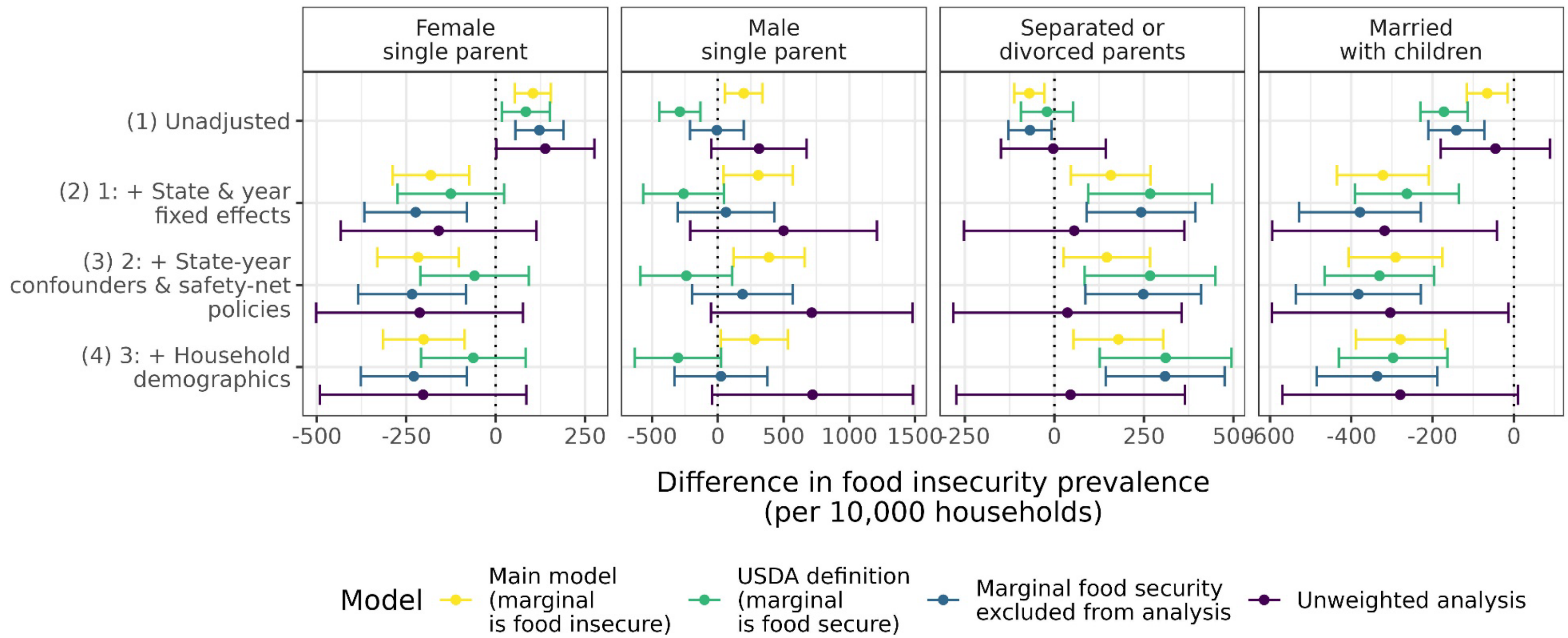
Point estimates and 95% confidence intervals from a linear probability model comparing models with increasing adjustment sets: (1) unadjusted; (2) model 1 plus adjustment for state and year fixed effects; (3) model 2 plus the state- and time-varying confounders and safety-net policies; and (4) model 3 plus household-level demographics. Standard errors were clustered at the household-level. The main model used the food security scale weights, the unweighted model used no weights, and the alternative definition of food insecurity model used the food security scale weights and classified those with marginal food security status as being food secure (as opposed to food insecure as in the main and unweighted models).

Supplemental Figure 3.11. Sensitivity analysis for educational attainment subpopulation results, comparing main survey weighted model with unweighted model and with model using the USDA definition of food insecurity among working aged households with children



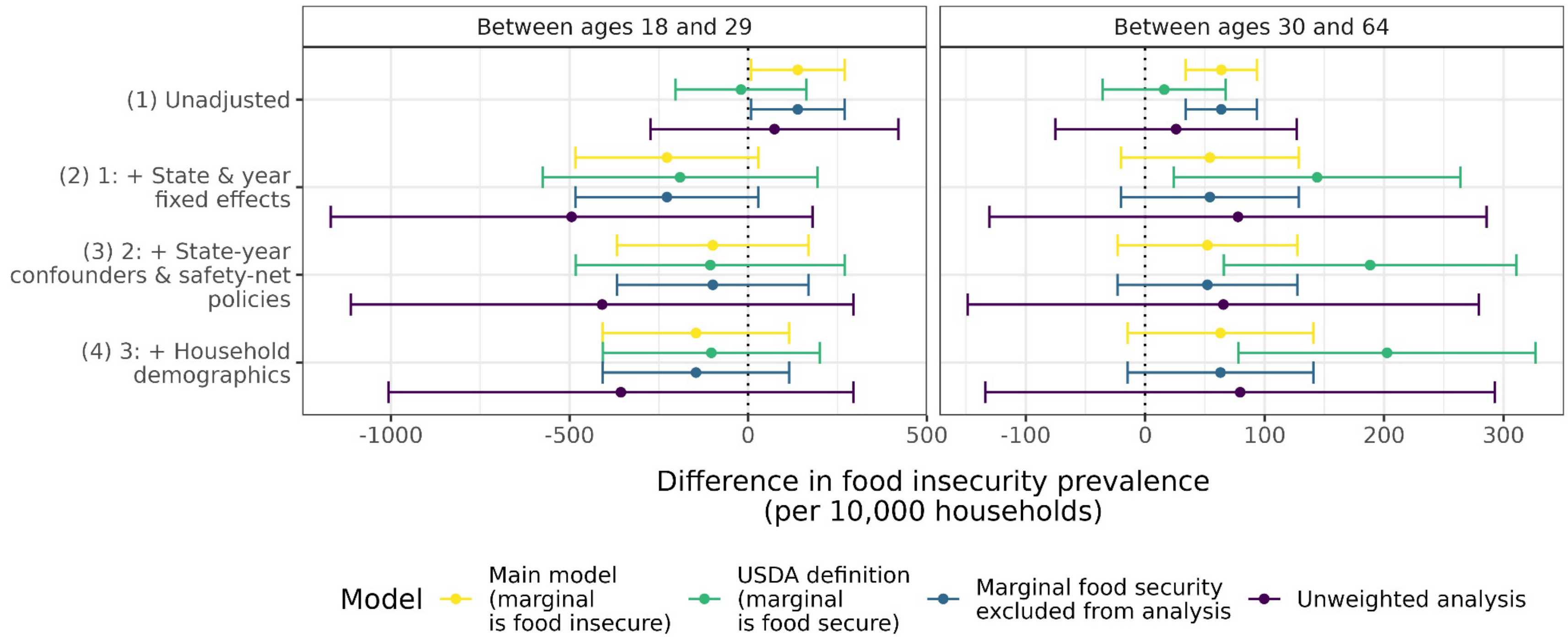
Point estimates and 95% confidence intervals from a linear probability model comparing models with increasing adjustment sets: (1) unadjusted; (2) model 1 plus adjustment for state and year fixed effects; (3) model 2 plus the state- and time-varying confounders and safety-net policies; and (4) model 3 plus household-level demographics. Standard errors were clustered at the household-level. The main model used the food security scale weights, the unweighted model used no weights, and the alternative definition of food insecurity model used the food security scale weights and classified those with marginal food security status as being food secure (as opposed to food insecure as in the main and unweighted models).

Supplemental Figure 3.12. Sensitivity analysis for family structure subpopulation results, comparing main survey weighted model with unweighted model and with model using the USDA definition of food insecurity for all working aged households with children



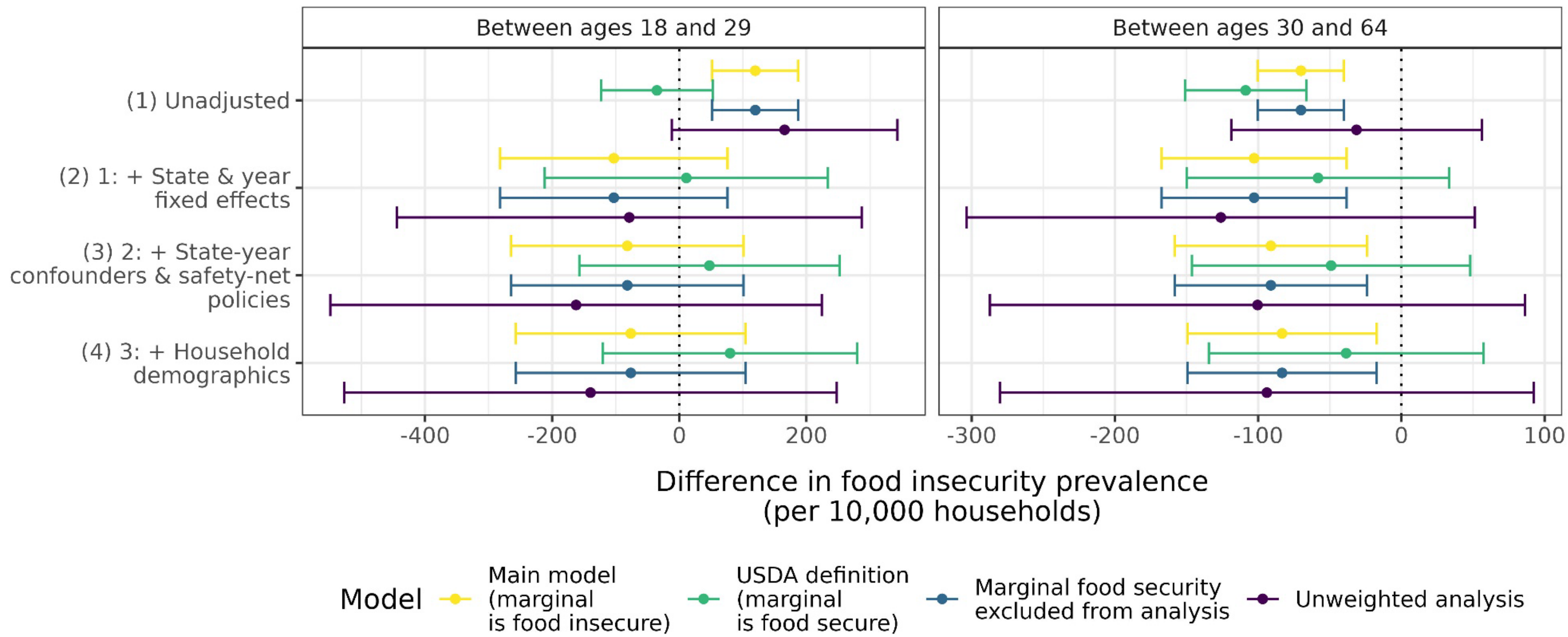
Point estimates and 95% confidence intervals from a linear probability model comparing models with increasing adjustment sets: (1) unadjusted; (2) model 1 plus adjustment for state and year fixed effects; (3) model 2 plus the state- and time-varying confounders and safety-net policies; and (4) model 3 plus household-level demographics. Standard errors were clustered at the household-level. The main model used the food security scale weights, the unweighted model used no weights, and the alternative definition of food insecurity model used the food security scale weights and classified those with marginal food security status as being food secure (as opposed to food insecure as in the main and unweighted models).

Supplemental Figure 3.13. Sensitivity analysis for young vs more experienced workers subpopulation results, comparing main survey weighted model with unweighted model and with model using the USDA definition of food insecurity among working aged households without children



Point estimates and 95% confidence intervals from a linear probability model comparing models with increasing adjustment sets: (1) unadjusted; (2) model 1 plus adjustment for state and year fixed effects; (3) model 2 plus the state- and time-varying confounders and safety-net policies; and (4) model 3 plus household-level demographics. Standard errors were clustered at the household-level. The main model used the food security scale weights, the unweighted model used no weights, and the alternative definition of food insecurity model used the food security scale weights and classified those with marginal food security status as being food secure (as opposed to food insecure as in the main and unweighted models).

Supplemental Figure 3.14. Sensitivity analysis for young vs more experienced workers subpopulation results, comparing main survey weighted model with unweighted model and with model using the USDA definition of food insecurity among working aged households with children



Point estimates and 95% confidence intervals from a linear probability model comparing models with increasing adjustment sets: (1) unadjusted; (2) model 1 plus adjustment for state and year fixed effects; (3) model 2 plus the state- and time-varying confounders and safety-net policies; and (4) model 3 plus household-level demographics. Standard errors were clustered at the household-level. The main model used the food security scale weights, the unweighted model used no weights, and the alternative definition of food insecurity model used the food security scale weights and classified those with marginal food security status as being food secure (as opposed to food insecure as in the main and unweighted models).

Chapter 4: Impacts of state-level minimum wages on rates of maltreatment-related death among children

4.1 Introduction

Child mortality due to maltreatment (abuse or neglect) has steadily increased in the United States (U.S.) over the past several years: according to data from the National Child Abuse and Neglect Data System (NCANDS), which aggregates information from state Child Protective Services (CPS) programs and welfare agencies, the number of reported child maltreatment deaths in children 18 years and younger rose from 460 in 2000 to 1,512 in 2019 (Supplemental Figure 4.1).[51]

Poverty is a well-established risk factor for child maltreatment. Studies have shown that children in lower socioeconomic households experience some type of maltreatment at more than 5 times the rate of other children,[150] and that a 1 percent increase in parental income is associated with a 5 percent decreased probability of maltreatment risk.[151] Research has also demonstrated consistent associations between neighborhood indicators of socioeconomic status (i.e. income levels, property values, poverty rates) and child maltreatment rates.[60] Given robust links between poverty and maltreatment, increasing household income may prevent child maltreatment[152,153] via two potential mechanisms. First, increasing household income directly raises the amount of financial resources available to families, allowing parents to provide children with basic needs including housing, food, and medical care, and to secure childcare when needed.[154] Provision of basic needs as well as adequate supervision are particularly important in preventing cases of neglect (characterized as the failure of parents to provide these resources thereby harming a child's health or safety).[155] Secondly, increasing household income may indirectly impact child maltreatment by decreasing parental stress and increasing availability of mental and emotional resources needed for healthy parenting.[156–158] This latter mechanism may be more relevant for physical abuse, since stress can erode parental emotional regulation and impulse control,[159] which may in turn increase risk for physical violence.[160]

Current approaches to address maltreatment are often reactive and hinge on families being reported to CPS, while structural approaches, such as those aimed at reducing family poverty and stress, present salient opportunities for intervention. A common state-level policy approach to poverty reduction is increasing the minimum wage. Previous studies have found that a $1 increase in minimum wage was associated with a 9.6% decrease in CPS reports of child neglect,[161] and with 0.28 fewer self-reported neglect events per caregiver per year.[162] Research also suggests that increases in minimum wage are most protective against child maltreatment reporting for children under age 3, with an attenuated effect for older children.[65] Despite child mortality's importance as a public health outcome, no studies, to our knowledge, have examined how minimum wages affect child maltreatment-related deaths.

In this study, we aimed to evaluate whether increases in state-level minimum wages reduce child maltreatment mortality rates, which may inform structural efforts to prevent child maltreatment.

4.2 Data and Methods

4.2.1 Sample and child maltreatment ascertainment

While NCANDS has historically been the key source of information on child maltreatment deaths in the U.S.,[163,164] it has well-known limitations. First, definitions of child maltreatment vary by state, and maltreatment deaths that are not reported to state child welfare agencies are not fully accounted.[155,164] Further, NCANDS may be subject to ascertainment and other sources of measurement bias leading to overrepresentation of low-income and other marginalized populations based on their race and ethnicity compared to true maltreatment incidence.[53–57] Lastly, fluctuations in annual state-level CPS funding mean that it is challenging to separate out systems-related changes due to inconsistent funding from true changes in underlying maltreatment rates, which in turn makes it difficult to compare trends over place and time.[165,166] For these reasons, death certificates have been proposed as one alternative approach for ascertaining child maltreatment deaths.

Death certificates are completed for each death in the U.S., are standardized across states,[164] and use International Classification of Diseases (ICD) codes to detail up to 20 antecedent conditions leading to the underlying cause of death.[167] Child maltreatment-related deaths may be identified in these data via ICD codes using two approaches. First, maltreatment-related deaths may be identified using ICD codes explicitly diagnosing child abuse or neglect (hereafter: “explicit” codes). However, these codes are underutilized,[168–171] may be subject to provider bias based on perceived risk,[172–174] and, when used on their own, may undercount true maltreatment-related mortality by upwards of 50-60%.[169,170,175] Previous work by Schnitzer et al. used hospital records to identify a set of ICD proxy codes for injuries predictive of abuse and neglect (hereafter: “proxy” codes)[176] which have been used to examine risk factors for and trends in child maltreatment injury.[177–179] Our second approach identifies maltreatment-related deaths via these proxy codes, regardless of whether there is an explicit child abuse or neglect ICD code on the death record. Proxy codes are less likely to suffer from underutilization and potential bias than explicit codes. In this paper, we apply both explicit and proxy codes to mortality data to identify a set of deaths among children likely related to abuse and/or neglect.

We obtained restricted-use national mortality data for 2000 to 2019 from the National Center for Health Statistics.[180] We included deaths among children less than 5 years old residing in one of the 50 U.S. states, or the District of Columbia (DC). This age cutoff was used because most proxy codes for maltreatment are specific to children under 5 years old, and previous findings suggest stronger impacts of minimum wage increases on younger children.[65]

We included deaths where at least one contributing cause was either (i) an explicit code for physical abuse, neglect, or maltreatment (Supplemental Table 4.1), or (ii) a proxy code for an injury predictive of physical abuse or neglect, as identified by Schnitzer et al[176] (Supplemental Table 4.2; see Supplemental Material for details on how these proxy codes were identified and modified). Since sexual abuse accounts for few maltreatment-related deaths, we excluded related codes.

4.2.2 Outcome: child maltreatment-related death rates

Maltreatment-related child deaths were aggregated by state, year, and age category (less than 1 year old vs. 1-4 years old). We calculated separate counts for deaths identified using (i) explicit codes only, (ii) proxy codes only, and (iii) either an explicit or proxy code. To calculate death rates, we obtained population estimates for each state-year-age combination.[181]

4.2.3 Exposure: state minimum wage

We obtained federal- and state-level minimum wage data from 2000 to 2019 from the University of Kentucky Center for Poverty Research,[85] and confirmed dates of minimum wage changes using state-government websites. For years when minimum wage changes occurred, we used a weighted average of the pre- and post-change amounts to reflect the fraction of the year the new wage was in effect. To account for inflation and changes in purchasing power over the 20-year study period, annual nominal minimum wage dollar values were converted to real 2019 dollars using the Consumer Price Index.[87] Since most employees are governed by The Fair Labor Standards Act and entitled to the higher of the state or federal minimum wage,[86] we defined effective minimum wage as the maximum of the annual state and federal minimum wage, converted to real 2019 dollars.

4.2.4 Covariates

4.2.4.1 State- and time-varying demographic confounders

The following state- and time-varying confounders were identified via a directed acyclic graph (Figure 4.1): annual unemployment rate (%),[85] annual poverty rate (%),[85] racial composition (% of population identifying as Non-Hispanic White),[182] age composition (% of population under 18 years old),[182] average per-capita income (nominal $),[183] and binary political leaning, which was classified based on political affiliation of the state governor (democratic yes/no).[85] For DC, political leaning was coded based on majority political party of elected members in the Council of the District of Columbia. To ensure temporality, demographic confounders from the year prior to the minimum wage measure were used.

4.2.4.2 State- and time-varying policy confounders

To account for the impact of poverty alleviation programs that changed concurrently with minimum wage (Figure 4.1), we included the following time-varying, state-level policies: Medicaid expansion under the Affordable Care Act (in effect for state-year, yes/no),[184] state Earned Income Tax Credit (EITC) rate,[85] and paid family leave (in effect for state-year, yes/no).[185]

4.2.5 Statistical Analysis

We leveraged differences in the dollar amount of effective state minimum wages to estimate the effect of a $1 increase in effective minimum wage on the maltreatment-related death rate in children less than 5 years old. We used state fixed effects to control for confounding by factors that varied across states, and year fixed effects to control for shared secular trends. We accounted for differences in death rate trends by age (Figure 4.2, Panel A) by adjusting for age in all models. Because we were interested in absolute scale measures, we used a linear regression with robust standard errors to compute incidence rate differences and 95% confidence intervals (95%CI) to estimate the effect of within-state changes in the minimum wage on within-state changes in child maltreatment-related mortality rates. We included 4 nested models, with increasing adjustment sets: (1) adjusted only for age; (2) model 1 plus adjustment for state and year fixed effects; (3) model 2 plus demographic confounders; (4) model 3 plus policy confounders (equation 4.1). We also calculated separate effects for deaths identified via explicit codes only, proxy codes only, and those identified by either an explicit or proxy code.

$$y_{st} = \beta_0 + \beta_1 * MW_{st} + \beta_2 * A_{st} + \beta_3 * \boldsymbol{S}_s + \beta_4 * \boldsymbol{Y}_t + \beta_5 * \boldsymbol{X}_{st} + \beta_6 * \boldsymbol{P}_{st} + \varepsilon_{st} \qquad \text{(Eq. 4.1)}$$

Where: y_{st} is the child maltreatment-related death rate for state s in year t; β_0 is the intercept; MW_{st} is the effective minimum wage for state s in year t with β_1 denoting the policy effect of interest; A_{st} is a binary variable denoting whether or not the state-year death rate is specific to infants less than 1 year old vs children between the ages of 1 and 4, with β_2 denoting the age-specific effect; $\boldsymbol{S}_s$ is a vector of indicator variables for each state s with β_3 indicating each state fixed effect; $\boldsymbol{Y}_t$ is a vector of indicator variables for each year t with β_4 indicating each *year fixed effect;* $\boldsymbol{X}_{st}$ *is a vector of the state- and time-varying demographic confounders (Figure 4.1) with* β_5 *representing the coefficients on these confounders;* $\boldsymbol{P}_{st}$ *is a vector of the state-and time-varying policy confounders (Figure 4.1) with* β_6 *representing the coefficients on these policies; and* ε_{st} *is residual state-year level variation.*

4.2.6 Subpopulation Analyses

We examined heterogeneity in effect estimates by race and ethnicity as listed on the death certificate. We aggregated all child maltreatment-related deaths to the state-year-age-race/ethnicity level and used stratified linear regression with robust standard errors to calculate race-specific effects among Non-Hispanic White, Non-Hispanic Black, and Hispanic subgroups, using the same four adjustment sets as the main model.

4.2.7 Sensitivity Analyses

We conducted multiple sensitivity analyses to verify the reliability of our results and evaluate the impact of analytic choices.

First, we excluded DC, a non-state, from our main model.

Second, although our main model was not a difference-in-differences model, we were nonetheless concerned that the kind of biases that arise in two-way fixed effects models which use both time and state fixed effects in the difference-in-differences context when staggered adoption and heterogenous or dynamic treatment effects are present[4–7] (See Appendix B for detailed discussion) could be induced in our main model as well (since minimum wage changes are staggered and may have heterogenous and/or dynamic treatment effects). We thus explored an alternative linear hybrid fixed effects model (equation 4.2) which is not subject to these specific biases. The hybrid model included state random effects, state- and year-specific effective minimum wage means, and an autoregressive correlation structure. The addition of state- and year-specific exposure means controlled for fixed differences between states and years (respectively) that may be correlated with minimum wages, effectively controlling for between-cluster confounding.[8] Like our main fixed effects analysis, we specified four versions with increasing adjustment sets: (a) adjusted only for age; (b) model a with the addition of state and year effective minimum wage means; (c) model b plus demographic confounders; (d) model c plus policy confounders.

$$y_{st} = \beta_{00} + \beta_{0s} + \beta_1 * MW_{st} + \beta_2 * A_{st} + \beta_3 * \overline{MW}_s + \beta_4 * \overline{MW}_t + \beta_5 * \boldsymbol{X}_{st} + \beta_6 * \boldsymbol{P}_{st} + \varepsilon_{st} \quad \text{(Eq. 4.2)}$$

Where: y_{st} *is the child maltreatment-related death rate for state s in year t;* β_{00} *is the intercept representing the grand mean;* β_{0s} *is the random effects state-specific intercept;* MW_{st} *is the effective minimum wage for state s in year t with* β_1 *denoting the policy effect of interest;* A_{st} *is a binary variable denoting whether or not the state-year death rate is specific to infants less* *than 1 year old vs children between the ages of 1 and 4, with β_2 denoting the age-specific effect; $\overline{MW}_s$ is the average minimum wage for state s across all years with β_3 indicating the coefficient for this term; $\overline{MW}_t$ is the average minimum wage for year t across all states with β_4 indicating coefficient for this term; $\boldsymbol{X}_{st}$ is a vector of the state- and time-varying demographic confounders (Figure 4.1) with β_5 representing the coefficients on these confounders; $\boldsymbol{P}_{st}$ is a vector of the state-and time-varying policy confounders (Figure 4.1) with β_6 representing the coefficients on these policies; and ε_{st} is residual state-year level variation.*

Third, we tested robustness to variations in the exposure timing and looked at the following alternate minimum wage specifications: minimum wage as of January 1st of each year, lagged minimum wage changes as of January 1st of the previous year, and pre-emptive minimum wage changes as of January 1st of the following year.

Last, we restricted our analysis to proxy code deaths in infants less than 1 year old, whose injuries were most likely to be maltreatment-related, as it is less plausible these types of injuries would be due to anything other than abusive or neglectful caregiver behavior. We further restricted the analysis to head injury deaths (skull vault fracture, retinal hemorrhage, traumatic subdural hemorrhage, traumatic subarachnoid hemorrhage, other/unspecified intracranial hemorrhage) among infants only for the same reason.

All analyses were performed in R version 4.1.3 (2022-03-10). This study was not considered human subjects research and no institutional review board approval was required.

4.3 Results

4.3.1 Descriptive statistics

Over the 20-year study period, we identified 24,025 child maltreatment-related deaths, corresponding to a rate of 6.05 deaths per 100,000 children under 5 years old. Trends over time varied by age and racial ethnicity (Figure 4.2). Maltreatment-related death rates were lower among children ages 1-4 compared to infants, and higher among non-Hispanic Black children than Hispanic and non-Hispanic White children.

From 2000 to 2019, the effective minimum wage remained stagnant or decreased in 22 states, whilst 22 states experienced an effective increase of at least $1 per hour (Supplemental Figure 4.2); the change in effective minimum wage over the study period ranged from a $0.40 decrease in 21 states to a $3.46 increase in California and a $4.50 increase in the District of Columbia (Supplemental Figure 4.3). States with higher minimum wages tended to be majority democratic with more generous poverty alleviation programs and slightly higher per capita income compared to states that followed the federal standard (Table 4.1).

4.3.2 Results from main model analysis

Models adjusted only for age (Model 1) estimated a small protective association of a $1 increase in minimum wage on child maltreatment-related fatalities ranging from -0.8 deaths per 100,000 children [95%CI: (-1.1, -0.5)] among deaths identified via combined proxy or explicit codes to -0.3 deaths per 100,000 children [95%CI: (-0.4, -0.2)] for deaths identified via explicit codes only (Figure 4.3, Supplemental Table 4.3). This finding is congruent with descriptive plots that show general decreasing trends in maltreatment deaths in states with higher or rising minimum wages (Supplemental Figure 4.4).

Adding state and year fixed effects (Model 2) attenuated all estimates towards the null: 0.01 deaths per 100,000 children [95%CI: (-0.5, 0.5)] for deaths identified via combined proxy or explicit codes and -0.09 deaths per 100,000 children [95%CI: (-0.3, 0.1)] for deaths identified via explicit codes only.

Controlling for demographic and policy confounders (Models 3 and 4) had little additional impact on the effect estimates, and using the preferred fully adjusted model 4, we found no effect of state-level minimum wages on child maltreatment-related death rates when combined explicit or proxy codes were used to identify deaths [-0.1 deaths per 100,000 children [95%CI: (-0.6, 0.4)]. Results from models 3 and 4 were similar when only explicit codes or only proxy codes were used for death identification.

4.3.3 Results from subpopulation analyses

Point estimates from fully adjusted models (Model 4) varied slightly across racial ethnicity groups (Figure 4.4, Supplemental Table 4.4), but were mostly close to the null with overlapping confidence intervals.

Results were imprecise but suggestive of potential harmful effects of increased minimum wages among non-Hispanic Black children when proxy codes were used for death identification [2.9 deaths per 100,000 children, 95%CI: (-0.5, 6.3)]. In contrast, fully adjusted point estimates for the maltreatment-related death rate among Hispanic children suggested consistently protective, if imprecise, effects regardless of whether proxy or explicit codes were used for death identification. Increases in minimum wage did not appear to impact maltreatment-related deaths among non-Hispanic White children, with consistent null point estimates across fully adjusted models.

4.3.4 Results from sensitivity analyses

Sensitivity analyses (Supplemental Figures 4.5 - 4.8) did not materially alter results, especially for adjusted models.

4.4 Discussion

Our study harnessed variation over 20 years of state-specific minimum wages to estimate impacts on child maltreatment-related mortality. We did not find evidence that changes to minimum wage affected child maltreatment-related death rates overall, but estimates suggested potential heterogeneity by race and ethnicity.

When states did increase their (unadjusted/nominal) minimum wage, they did so by $0.51 on average. This translates to approximately $1,020 of nominal, additional pre-tax income for the average full-time minimum wage worker each year. While this isn't a lot of money, findings from previous studies have linked smaller increases in household income to reduced involvement of child welfare agencies. In Wisconsin, increasing Temporary Assistance to Needy Families (welfare) payments by only $100 resulted in a 2% reduction in state child welfare system involvement,[62] while a $1,000 increase in the Earned Income Tax Credit (EITC) resulted in a 8-10% reduction in self-reported CPS involvement among low-income, single mother families.[61] Prior minimum wage studies have also linked increased minimum wage to reductions in child neglect: in response to a $1 increase in minimum wage, Raissian and Bullinger estimated a 9.6% decrease in CPS reports of neglect,[63] and Ash et. al. estimated 0.39 fewer annual self-reported maternal neglect events per family in children under 3 years old.[65] In contrast to these prior findings, our estimated effects of increased minimum wages on child maltreatment-related mortality via overall and race-specific models were all close to the null in the overall group and for non-Hispanic White children.

There are several reasons why minimum wages may not affect maltreatment-related mortality. While minimum wages changed frequently throughout the study period, the effective minimum wage in several states did not keep pace with inflation and may have been too modest to materially alter pathways leading to child maltreatment mortality. Further, not all workers benefit from state-level minimum wage policies – for example, the federal minimum rate for tipped workers has remained frozen at $2.13 since 1996, and only 7 states have completely eliminated a lower wage for these employees.[186] Approximately 80% of food and beverage industry workers are low-wage workers,[187] and these individuals may not have seen their wages increase during the study period if they received tips. Even for families who experienced increased income due to higher wages, the possible protective effects of these additional resources may have been offset by disqualification from or reduction in other social benefit programs. For example, both the Supplemental Nutrition Assistance Program and the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) have income eligibility cutoffs. It is plausible that, for some families, wages increased enough for them to be disenrolled from these programs, but not enough to make up for the loss of benefits, thereby dampening any positive effect of higher minimum wages. That said, many of the challenges described above should similarly affect prior studies examining minimum wage and maltreatment, and thus these explanations are unlikely to explain the inconsistencies between our findings and prior research. While the previous studies focused on reported instances of child maltreatment (either via CPS or self-report), our study examines maltreatment-related morality, a more rare and severe outcome. Specifically, it is possible that increasing the minimum wage reduces milder forms of abuse and neglect, thus reducing CPS reports but not mortality. It is also possible that increases in minimum wage reduce CPS reports by reducing interactions between families and mandated reporters (e.g., through reduced reliance on safety net programs) – a mechanism which would not extend to mortality.

The suggested harmful, although imprecise, effect estimates of minimum wage increases on maltreatment-related mortality among non-Hispanic Black children when proxy codes were used in death identification were unexpected. While research has shown that increases in minimum wage tend to have minimal effects on employment overall,[22,24] there is also evidence which suggests that higher minimum wages could lead to job loss among some types of workers including restaurant workers[104] and those working in tradeable sectors (e.g. manufacturing, agricultural, IT services).[188] It is possible that Black families are more affected by negative ramifications of increased wages, leading to higher maltreatment-related mortality, and this hypothesis warrants further investigation. Further, documented disparities and discrimination in the administration of public assistance programs, especially for Black applicants, may mean that these families are disproportionately unable to access and may even lose social safety net benefits when their income changes, despite eligiibility.[105–107] Additional research on the interactive effects of minimum wage policies with other safety net programs may help to elucidate pathways of disparities. Also, since maltreatment mortality is more rare and severe compared to maltreatment injury, it would be useful to see if similar racial disparities in the impact of minimum wages on maltreatment-related hospitalizations hold true.

This study has limitations. First, it is unable to determine whether individual families experiencing minimum wage changes are the same ones who experienced maltreatment mortality. Second, cause of death is determined in some U.S. counties by medical examiners (who are trained in forensic pathology) and in other counties by coroners (who are elected officials, often not physicians and not trained in death investigations).[189] Inconsistencies in how deaths were classified based on the training of the person filling out the death certificate may have led to misclassification within the ICD codes used to identify maltreatment-related mortality. Third, although proxy codes used to identify deaths suggestive of physical abuse or neglect have been validated in the context of maltreatment morbidity,[176] they have not been validated for mortality. It is possible that conditions indicative of maltreatment morbidity differ from those indicative of maltreatment mortality. That said, for an injury highly correlated with maltreatment morbidity to be only weakly correlated with maltreatment mortality would require that non-maltreatment-related causes of that injury to disproportionately result in death, which seems unlikely.

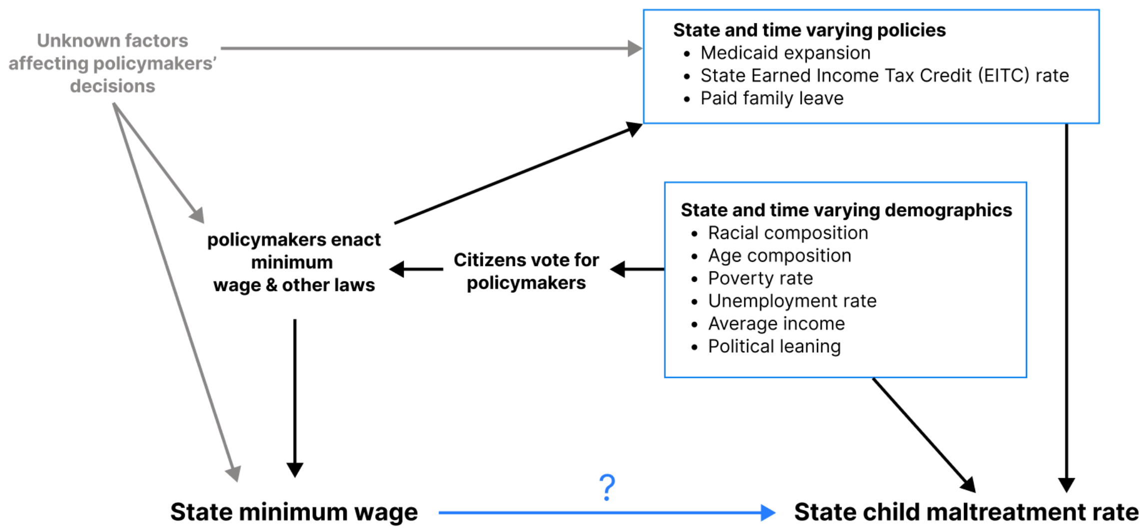
This study also has several strengths. Despite some potential misclassification, mortality data provide an important complement and alternative to CPS identification of maltreatment fatalities. The use of combined explicit and proxy ICD codes is likely less subject to the ascertainment bias (i.e. racial and systems biases) that may influence who is investigated and determined culpable of maltreatment,[53–57] and are not affected by variations in CPS system funding, processes, or capacity, which can make CPS data difficult to compare over time and across geographies.[165,166] Additionally, our analytic model included fixed effects to control for differences between states and shared time trends, and adjusted for time-varying state demographic characteristics and changing co-occurring poverty alleviation policies. These controls substantially reduce confounding bias in the estimate of the effect of state-level minimum wages on child maltreatment-related mortality rates.

4.5 Conclusions

This study used child maltreatment explicit and proxy ICD codes in death certificates to estimate the effect of wage-setting policies on child maltreatment-related mortality. To augment the existing body of evidence on policies and maltreatment more generally,[61,190–193] future work might consider how these ICD codes may be used to study how other policy interventions – such as paid family leave, Medicaid expansion, and a more generous child tax credit, as well as their interactions – impact child maltreatment-related mortality, hospitalizations (for which there may be more power), and disparities by race and ethnicity. Identifying which structural-level factors show the most evidence of preventing maltreatment morbidity and mortality can provide support for more widespread policy interventions to improve and extend the lives of the most vulnerable.

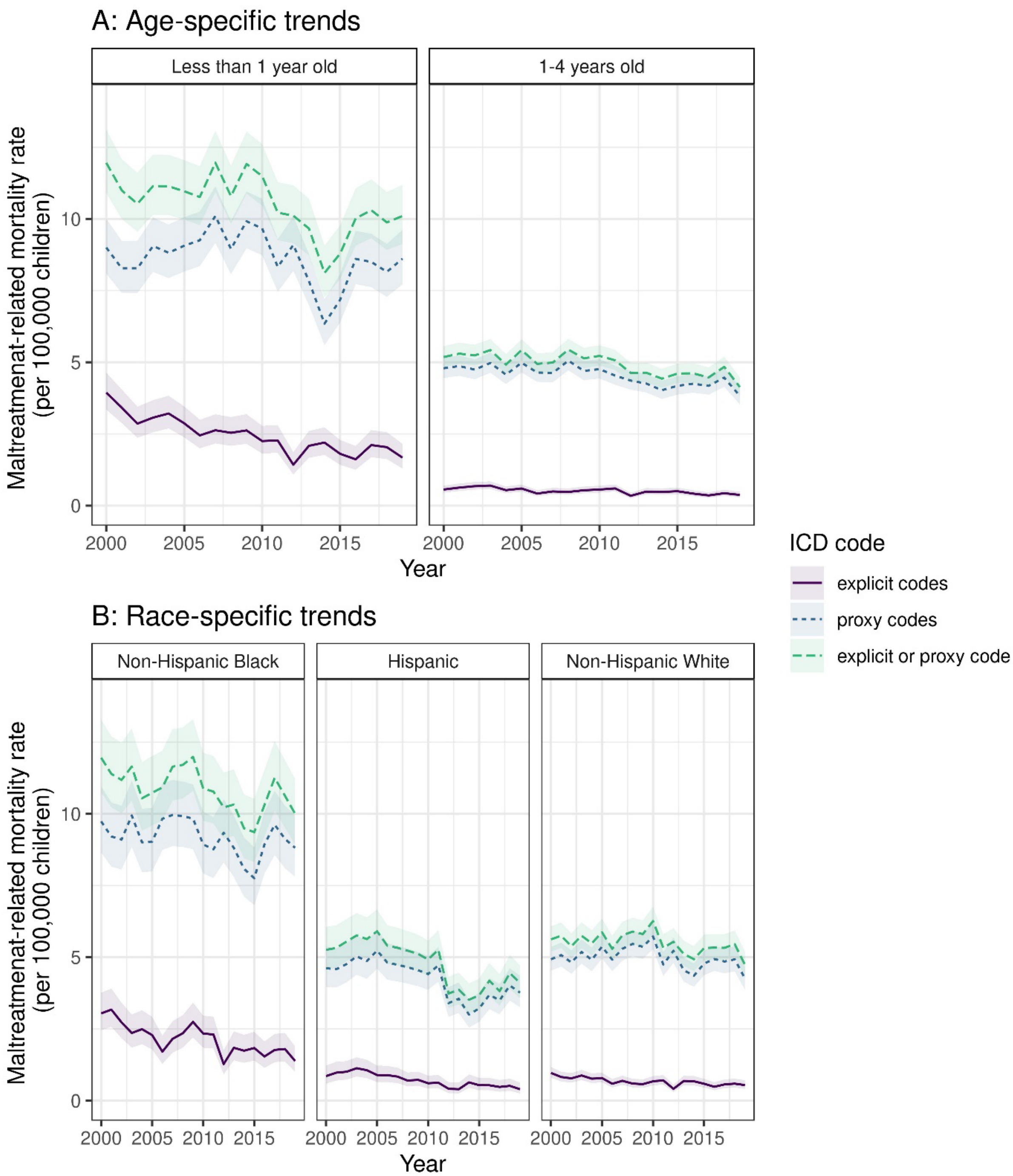
4.6 Tables and Figures

Figure 4.1 Directed acyclic graph depicting key variables determining state-level child maltreatment death rates



Boxed nodes denote variables adjusted for in the analysis.

Figure 4.2 Age and race trends in child maltreatment-related death rates, with 95% confidence intervals, colored by type of ICD code used to identify deaths



Child maltreatment-related death rates (per 100,000 children) are plotted over time, colored by the type of ICD code used to identify the deaths. 95% confidence intervals for each death rate are depicted via the same colored, semi-transparent ribbon.

Table 4.1: State demographic and policy characteristics stratified by whether the state's minimum wage laws follow the federal standard, track with inflation, or otherwise exceed the federal standard at some point during the study

	State minimum wage follows federal standard[a]	**State minimum wage tracks with inflation by 2019**[b]	**State minimum wage exceeds federal standard at some point during study**
# of states	16	14	21
States	AL*, GA, ID, IN, KS, KY, LA*, MS*, ND, OK, SC*, TN*, TX, UT, VA, WY	AK, AZ, CO, DC, ME, MN, MT, NJ, NY, OH, OR, SD, VT, WA	AR, CA, CT, DE, FL, HI, IA, IL, MA, MD, MI, MO, NC, NE, NH, NM, NV, PA, RI, WI, WV
% of population under age 18 (average†)	25.2%	23.4%	23.5%
% of population identifying as Non-Hispanic White (average†)	74.0%	75.4%	71.1%
Average per capita income	$36,229	$42,280	$40,491
Unemployment rate (average†)	5.4%	5.6%	5.6%
Poverty rate (average†)	13.8%	12.0%	12.0%
# of state years with democratic governor (average†)	5.4	10.5	10.0
# and % of states with a state Earned Income Tax Credit (EITC) rate	6 (37.5%)	10 (71.4%)	14 (66.7%)
State Earned Income Tax Credit (EITC) rate (average†)	2.9%	12.3%	6.7%
# and % of states implementing Medicaid expansion	5 (31.3%)	13 (92.9%)	16 (76.2%)
Total # of state-years with active Medicaid expansion in effect	22	70	95
# and % states with Paid Family Leave	0 (0%)	3 (21.4%)	3 (14.3%)
Total # of state-years with active Paid Family Leave in effect	0	14	27

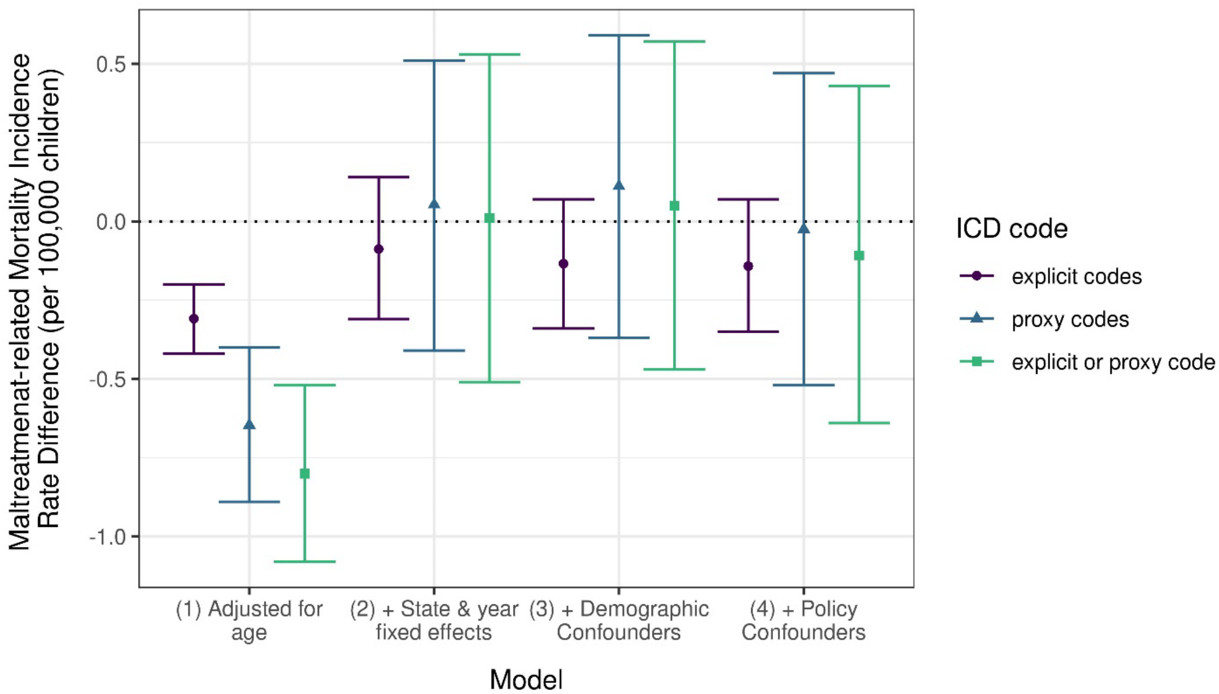
[a] *These states either had no state-level minimum wage, set their state minimum wage to follow the federal standard, or had wages which fell below the federal floor, and thus effectively allowed the federal wage to take effect for the duration of the study period.*

[b] *At some point before the end of the study period (2019), the minimum wage in these states became indexed to inflation and was thus legislated to change each year based on inflation.*

** Indicates state has no state-level minimum wage.*

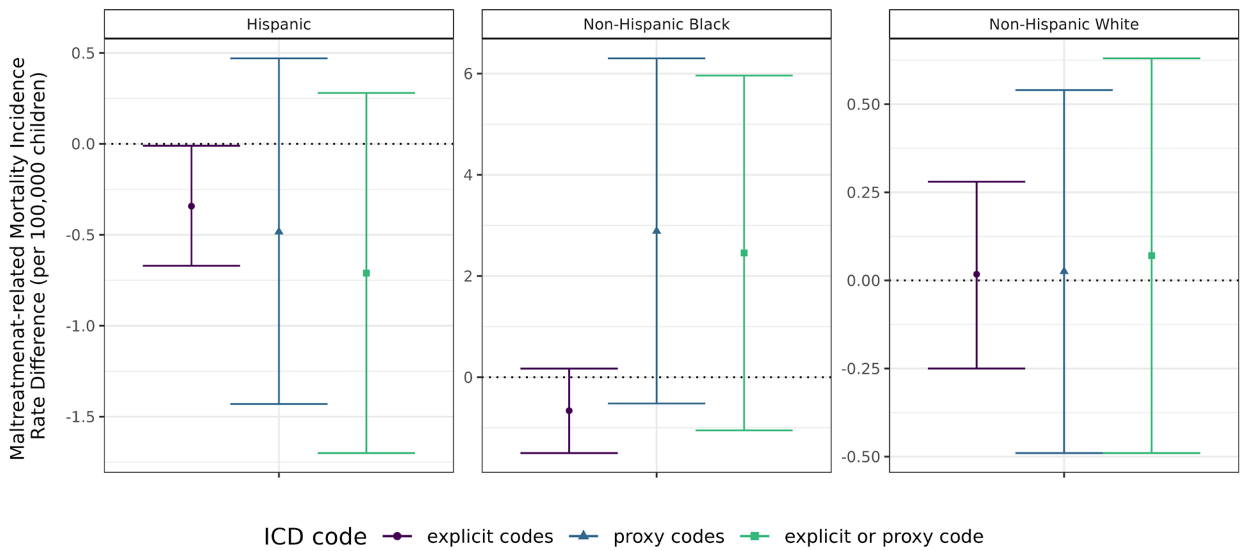
[†] *Averages are determined by first calculating the state-specific average over all study years, and then averaging over all states in each exposure category.*

Figure 4.3. Incidence rate difference point estimates (per 100,000 children) and 95% confidence intervals for the effect of a $1 increase in minimum wage on child maltreatment-related death rates, colored by type of ICD code used to identify deaths



Estimates are from a linear fixed effects model with increasing adjustment sets: (1) adjusted only for age; (2) model 1 with the addition of state and year fixed effects; (3) model 2 plus demographic confounders; (4) model 3 plus policy confounders.

Figure 4.4. Fully adjusted (Model 4) incidence rate difference point estimates (per 100,000 children) and 95% confidence intervals for the effect of a $1 increase in minimum wage on child maltreatment-related death rates, colored by type of ICD code used to identify deaths and stratified by race and ethnicity



Estimates are from a linear fixed effects model which included adjustment for age, state and year fixed effects, demographic confounders, and policy confounders.

4.7 Supplemental Material

4.7.1 Use of proxy codes to identify maltreatment-related childhood injuries

Detailed information about how proxy codes were identified in Schnitzer et al.'s initial study are available elsewhere,[194] but briefly, medical records from hospital discharge and emergency department visits of children suspected of being maltreated were reviewed to assess the injuries or illnesses diagnosed at the visit.

Sixty-eight ICD codes were indicated as suggestive of child maltreatment; for these ICD codes, over 66% of visits with each code were independently verified to be maltreatment-related when combined with age restrictions and exclusion codes (e.g., retinal hemorrhage in children under 3 years old, not resulting from a car accident or blood disease). Codes included visits for assault and specific fractures as proxies for physical abuse, drowning and poisoning as proxies for neglect, among others. Age restrictions for most codes were for children under age 5, and thus we restricted the data to this population.

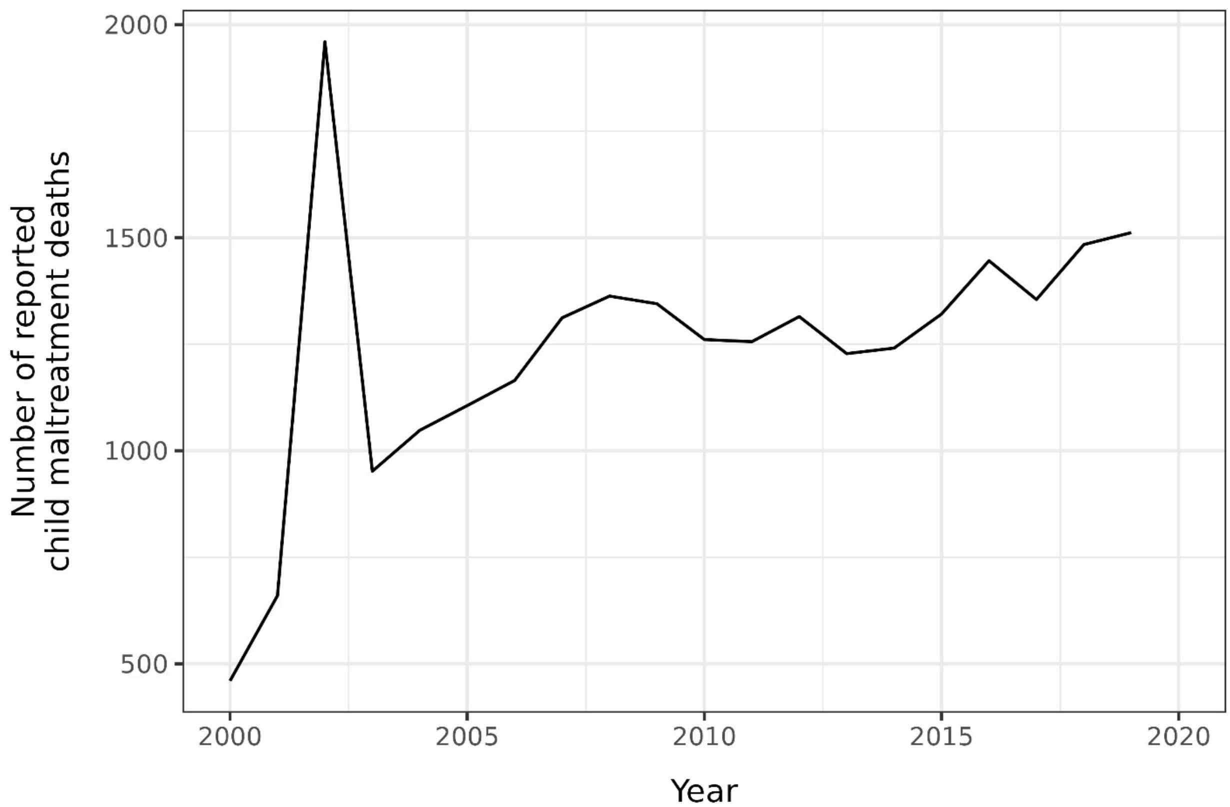
Since the ICD codes published by Schnitzer et al., are specific to ICD-9-CM (ICD Clinical Modification, 9th revision), an ICD variant used by U.S. hospitals, a modified crosswalk developed by Dougall et al., and made available via GitHub by Savinc,[195,196] (Supplemental Table 4.2) was used to translate these 68 ICD-9-CM codes (and any corresponding exclusion codes) to the ICD-10 (ICD, 10th revision) format used in mortality data.

We applied all age restrictions and exclusion codes associated with each proxy code condition.

Lastly, we excluded proxy codes suggestive of sexual abuse as it is an uncommon cause of death.

4.7.2 Supplemental Figures and Tables

Supplemental Figure 4.1. Number of child maltreatment reported deaths in children 18 years and younger from NCANDS, 2000-2019



Supplemental Table 4.1. Explicit child maltreatment ICD-10 codes

Contributing cause of death	ICD-10 codes
Neglect and/or abandonment	T740, Y06
Physical abuse	T741
Other maltreatment syndromes	T748, T749, Y07

Supplemental Table 4.2. Modified crosswalk of Schnitzer child maltreatment proxy codes

Condition	Original Schnitzer ICD-9-CM codes	Modified ICD-10 codes†	Age limit upper bound	Type of abuse
Assault	E965, E966, E968.2	X93-X96, X99, Y00	3	physical abuse
Assault, NOS	E968.9	Y09	3	physical abuse
Other/unspecified intracranial hemorrhage	853.0	S06.8	4	physical abuse
Retinal hemorrhage	362.81	H35.6	2	physical abuse
Rib fracture	807.0, 807.1	S22.30*†*, S22.31*†*	4	physical abuse
Scapula fracture	811	S42.1	4	physical abuse
Stomach injury	863.1	S36.31*†*	9	physical abuse
Traumatic subdural hemorrhage	852.2	S06.5	4	physical abuse
Undetermined intent, other means	E988	Y19, Y26, Y27, Y31-Y34	9	physical abuse
Accidental drowning, NOS	E910.9	W74	3	neglect
Bathtub drowning	E910.4	W65, W66	3	neglect
Burn of head	941	T20	4	neglect
Burn of leg	945	T24, T25	4	neglect
Burn of multiple sites	946	T29	4	neglect
Burn of trunk	942	T21	4	neglect
Dental caries*††*	521.0	K02	9	neglect

Table continues on next page

Drowning	994.1	T751	3	neglect
GI injury, NEC	863.8	S36.2, S36.8, S36.9	4	neglect
Heart or lung injury	861	S26, S27.3-S27.6	4	neglect
Household circumstances*††*	V60	Z59	9	neglect
Kidney injury	866	S37.0	4	neglect
Liver injury	864	S36.1	4	neglect
Other drowning	E910.8	W73	3	neglect
Other severe malnutrition	262	E43	9	neglect
Pelvic fracture	808	S32.1-S32.8, T02.1	4	neglect
Poisoning by drugs/Medicinals	960-979	T36-T50	4	neglect
Second-hand tobacco smoke*††*	E869.4	Z58.7	9	neglect
Solar radiation dermatitis*††*	692.7	L57.8	1	neglect
Swimming accident	E910.2	W67-W70	3	neglect
Traumatic pneumohemothorax	860	S27.0-S27.2	4	neglect
Unarmed fight, brawl	E960.0	Y04	3	neglect
Undetermined intent, firearm	E985	Y22-Y25	9	neglect
Undetermined intent, poisoning	E980	Y10-Y19	4	neglect
Intrathoracic injury, NEC	862	S277-S279	4	neglect or physical abuse
Skull vault fracture	800	S02.0	4	neglect or physical abuse
Small intestine injury	863.2, 863.3	S36.40, S36.41*†*	4	neglect or physical abuse
Spinal cord injury	952	S14.0, S14.1, S24.0, S24.1, S34.0, S34.1, T06.0, T06.1, T09.3	2	neglect or physical abuse
Spleen injury	865	S36.0	4	neglect or physical abuse

Table continues on next page

Traumatic subarachnoid hemorrhage	852.0	S06.6	4	neglect or physical abuse
Vertebral fracture	805	S12.0, S12.1, S12.2, S12.7, S12.9, S22.0, S22.1, S32.0, S32.7	4	neglect or physical abuse
Observation for abuse/neglect	V71.81	n/a *	9	neglect or physical abuse
Contusion of genital organs	922.4	S30.2	9	sexual abuse**
Genital herpes	054.1	A60	9	sexual abuse**
Gonococcal infection	098	A54	9	sexual abuse**
Observation after alleged rape	V71.5	Z04.4	9	sexual abuse**
Pelvic inflammatory disease, unspecified	614.9	N73.9	9	sexual abuse**

† Crosswalk obtained from Dougall et al. and Savic.[195,196] As some of the ICD-10 codes in the crosswalk were 5 digits long and we only had 4 digits available in our data, we made the following modifications: for rib fracture, S22.30 and S22.31 were replaced by S22.3; for stomach injury, S36.31 was replaced by S36.3; and for small intestine injury, S36.40 and S36.41 were replaced by S36.4.

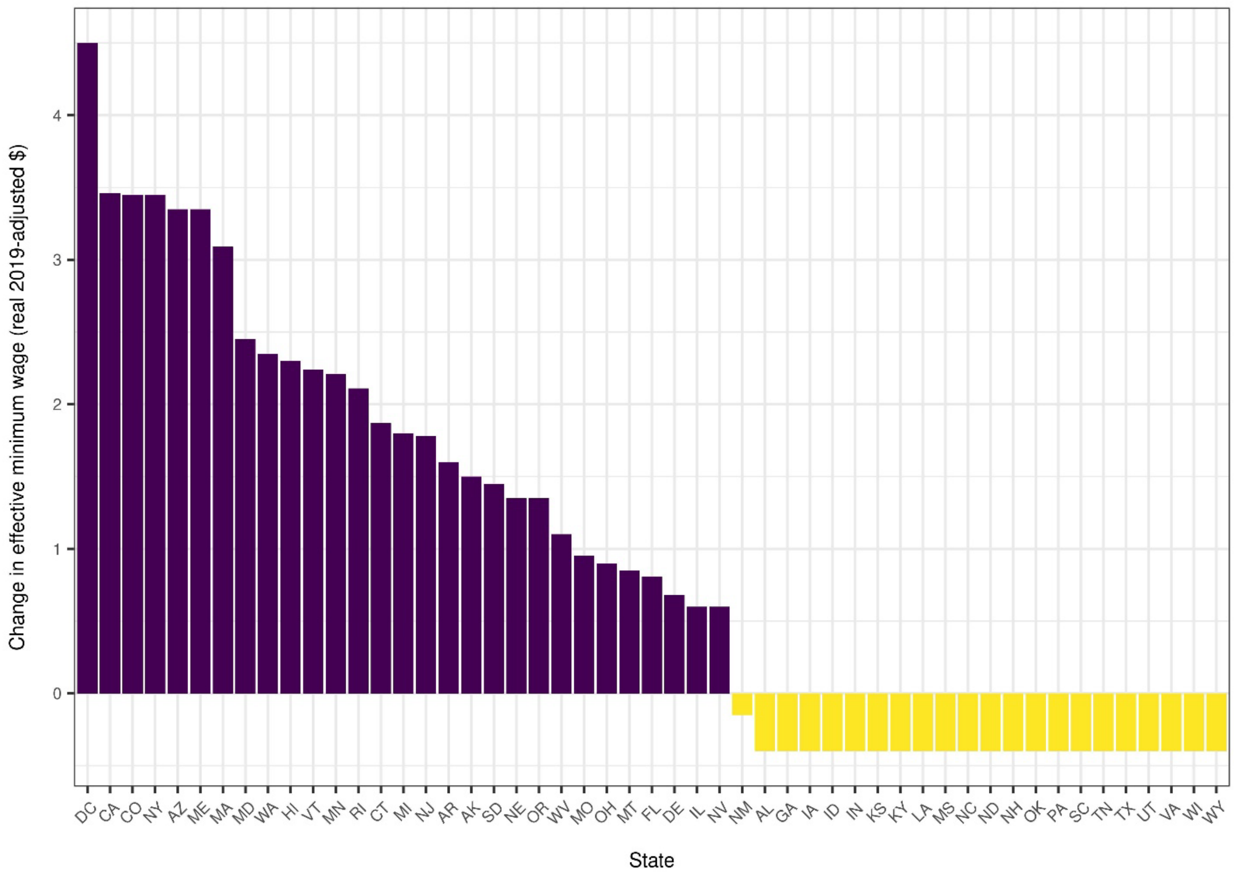
††While these conditions are less applicable to mortality, we retained them to maintain consistency with original proxy code research. None of the deaths in our study listed household circumstances, second-hand tobacco smoke, or solar radiation dermatitis as a contributing cause of death. There were 7 deaths included in our study for which dental caries was the only maltreatment-related condition, and for one of these, dental caries was listed as the main cause of death.

** Not included in this analysis as there is no equivalent ICD-10 code.*

*** Deaths suggestive of sexual abuse were not included in this study.*

Supplemental Figure 4.2. Trends in inflation-adjusted real state minimum wage (solid green line) and inflation-adjusted real federal minimum wage, 2000-2019 (dotted line)

Supplemental Figure 4.3. State-specific effective minimum wage change from 2000 to 2019

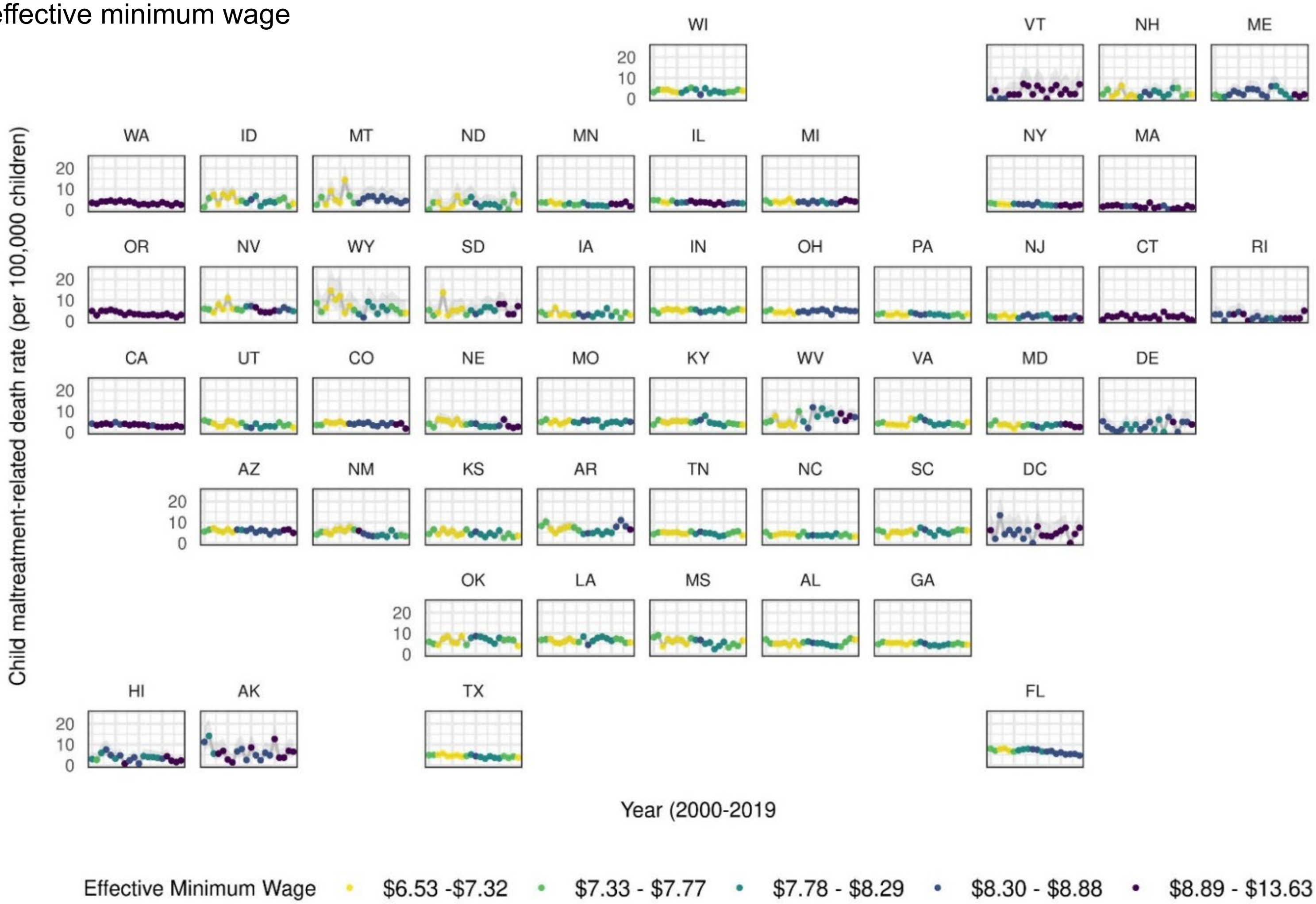


Effective minimum wage for each year was calculated as the maximum of the state and federal minimum wage in that year, converted to real 2019 dollars to account for inflation; wages which keep pace with or exceeded inflation are dark purple, while those which have not (effective minimum wage below $0) are denoted in light yellow.

Supplemental Table 4.3. Incidence rate differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on child maltreatment-related death rates, by type of ICD code used to identify deaths

Model	Incidence rate differences, deaths per 100,000 children (95% CI)		
	Explicit or proxy code *(24,025 deaths)*	**Explicit codes only** *(3,564 deaths)*	**Proxy codes only** *(21,278 deaths)*
(1) Adjusted for age	-0.80 (-1.08, -0.52)	-0.31 (-0.42, -0.20)	-0.65 (-0.89, -0.40)
(2) Adjusted for age + state and year fixed effects	0.01 (-0.51, 0.53)	-0.09 (-0.31, 0.14)	0.05 (-0.41, 0.51)
(3) Adjusted for age + state and year fixed effects + demographic confounders	0.05 (-0.47, 0.57)	-0.13 (-0.34, 0.07)	0.11 (-0.37, 0.59)
(4) adjusted for age + state and year fixed effects + demographic confounders + policy confounders	-0.11 (-0.64, 0.43)	-0.14 (-0.35, 0.07)	-0.31 (-0.52, 0.47)

Supplemental Figure 4.4. State-level maltreatment-related death rates (per 100,000 children), colored by magnitude of annual effective minimum wage



Child maltreatment-related death rates (per 100,000 children) are plotted as points, colored by the magnitude of the effective minimum wage in that state year where darker points represent higher values. Points are joined by a solid grey line to highlight trends. Confidence intervals for each death rate are depicted via grey ribbon.

Supplemental Table 4.4. Incidence rate differences and 95% confidence intervals for the effect of a $1 increase in minimum wage on child maltreatment-related death rates, by type of ICD code used to identify deaths, stratified by race and ethnicity

Explicit Codes Only				
	Incidence rate differences, deaths per 100,000 children (95% CI)			
Model	**All Race and Ethnicities** *(3,564 deaths *)*	**Non-Hispanic White** *(1,448 deaths)*	**Non-Hispanic Black** *(1,285 deaths)*	**Hispanic** *(662 deaths)*
(1) Adjusted for age	-0.31 (-0.42, -0.20)	-0.26 (-0.37, -0.16)	-0.30 (-0.70, 0.09)	-0.37 (-0.52, -0.21)
(2) Adjusted for age + state and year fixed effects	-0.09 (-0.31, 0.14)	0.04 (-0.19, 0.28)	-0.35 (-1.17, 0.46)	-0.29 (-0.59, 0.00)
(3) Adjusted for age + state and year fixed effects + demographic confounders	-0.13 (-0.34, 0.07)	-0.02 (-0.27, 0.24)	-0.35 (-1.13, 0.44)	-0.38 (-0.70, -0.06)
(4) adjusted for age + state and year fixed effects + demographic confounders + policy confounders	-0.14 (-0.35, 0.07)	0.02 (-0.25, 0.28)	-0.66 (-1.50, 0.17)	-0.34 (-0.67, -0.01)

Table continues on next page

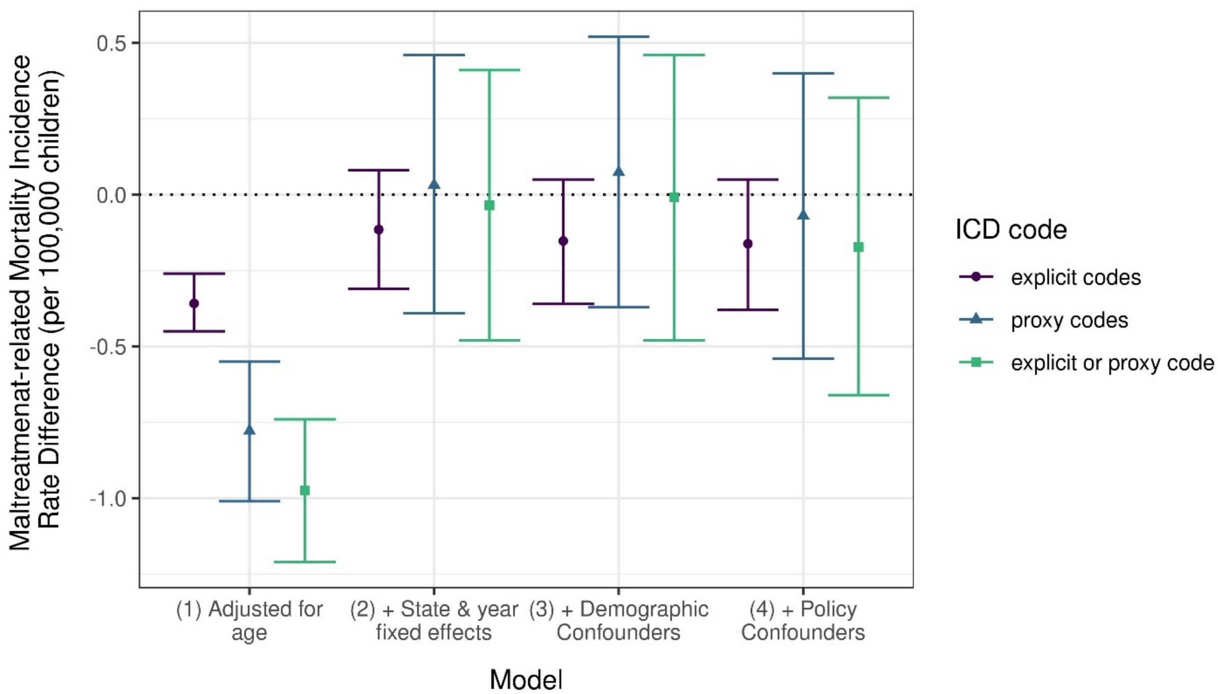
Proxy Codes Only				
	Incidence rate differences, deaths per 100,000 children (95% CI)			
Model	**All Race and Ethnicities** *(21,278 deaths*)*	**Non-Hispanic White** *(10,769 deaths)*	**Non-Hispanic Black** *(5,523 deaths)*	**Hispanic** *(4,032 deaths)*
(1) Adjusted for age	-0.65 (-0.89, -0.40)	-0.64 (-0.87, -0.41)	0.29 (-1.36, 1.94)	-0.57 (-1.09, -0.05)
(2) Adjusted for age + state and year fixed effects	0.05 (-0.41, 0.51)	0.17 (-0.27, 0.61)	2.84 (-0.48, 6.17)	-0.45 (-1.30, 0.39)
(3) Adjusted for age + state and year fixed effects + demographic confounders	0.11 (-0.37, 0.59)	0.19 (-0.30, 0.68)	2.82 (-0.47, 6.10)	-0.35 (-1.30, 0.59)
(4) adjusted for age + state and year fixed effects + demographic confounders + policy confounders	-0.31 (-0.52, 0.47)	0.03 (-0.49, 0.54)	2.89 (-0.52, 6.30)	-0.48 (-1.43, 0.47)

Table continues on next page

Explicit or Proxy Code				
	Incidence rate differences, deaths per 100,000 children (95% CI)			
	All Race and Ethnicities	**Non-Hispanic White**	**Non-Hispanic Black**	**Hispanic**
Model	*(24,025 deaths*)*	*(11, 884 deaths)*	*(6,521 deaths)*	*(4,544 deaths)*
(1) Adjusted for age	-0.80 (-1.08, -0.52)	-0.77 (-1.01, -0.53)	0.19 (-1.49, 1.88)	-0.80 (-1.34, -0.26)
(2) Adjusted for age + state and year fixed effects	0.01 (-0.51, 0.53)	0.22 (-0.25, 0.70)	2.59 (-0.82, 6.01)	-0.65 (-1.54, 0.24)
(3) Adjusted for age + state and year fixed effects + demographic confounders	0.05 (-0.47, 0.57)	0.21 (-0.32, 0.74)	2.65 (-0.71, 6.02)	-0.58 (-1.56, 0.40)
(4) adjusted for age + state and year fixed effects + demographic confounders + policy confounders	-0.11 (-0.64, 0.43)	0.07 (-0.49, 0.63)	2.46 (-1.05, 5.96)	-0.71 (-1.70, 0.28)

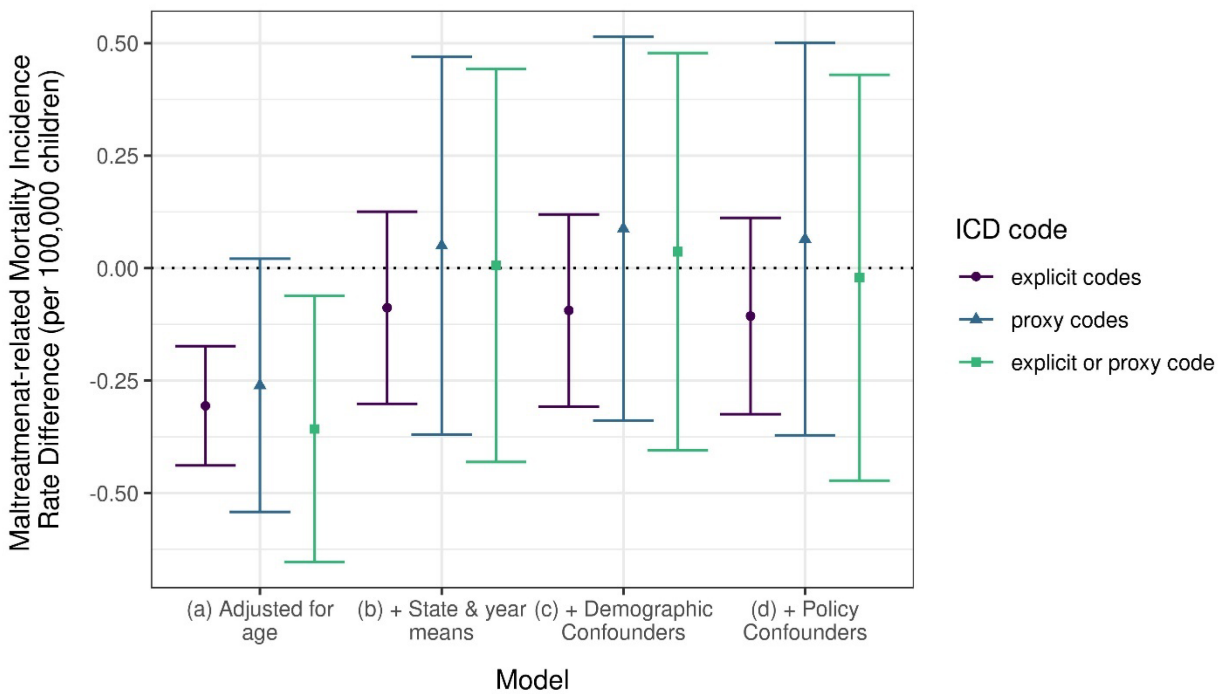
** The “All race and ethnicities model” also includes deaths among “other” and unknown race and/or ethnicity categories*

Supplemental Figure 4.5. Results of sensitivity analyses removing DC: incidence rate difference point estimates (per 100,000 children) and 95% confidence intervals for the effect of a $1 increase in minimum wage on child maltreatment-related death rates, colored by type of ICD code used to identify deaths



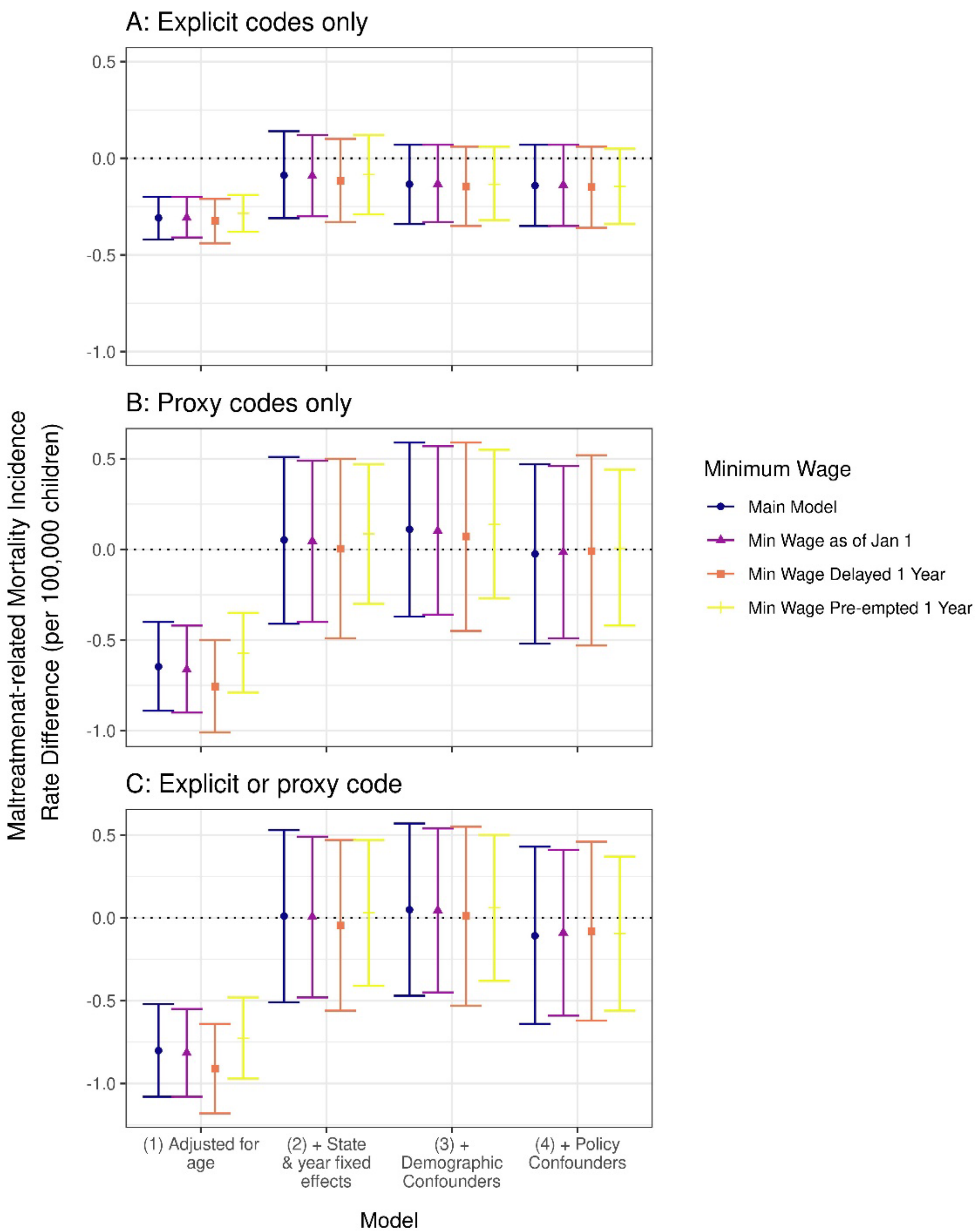
Estimates are from a linear fixed effects model with DC removed, comparing increasing adjustment sets: (1) adjusted only for age; (2) model 1 with the addition of state and year fixed effects; (3) model 2 plus demographic confounders; (4) model 3 plus policy confounders.

Supplemental Figure 4.6. Results of sensitivity analyses using an alternate hybrid fixed effects model: incidence rate difference point estimates (per 100,000 children) and 95% confidence intervals for the effect of a $1 increase in minimum wage on child maltreatment-related death rates, colored by type of ICD code used to identify deaths



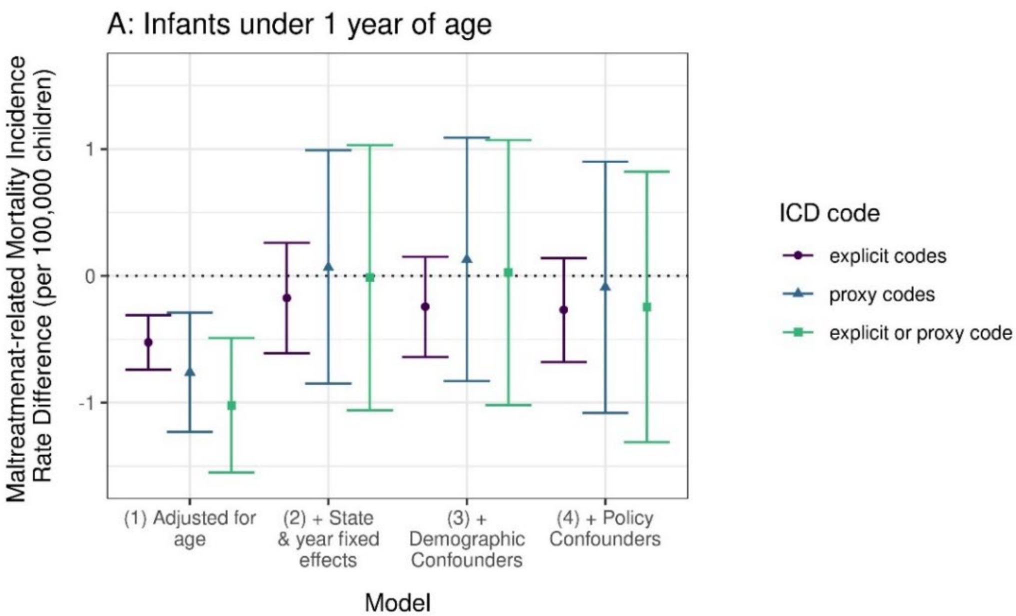
Estimates are from a hybrid fixed effects model which includes state random effects and an autoregressive correlation structure; four versions with increasing adjustment sets are compared: (a) adjusted only for age; (b) model a with the addition of state and year effective minimum wage means; (c) model b plus demographic confounders; (d) model c plus co-occurring poverty alleviation policies.

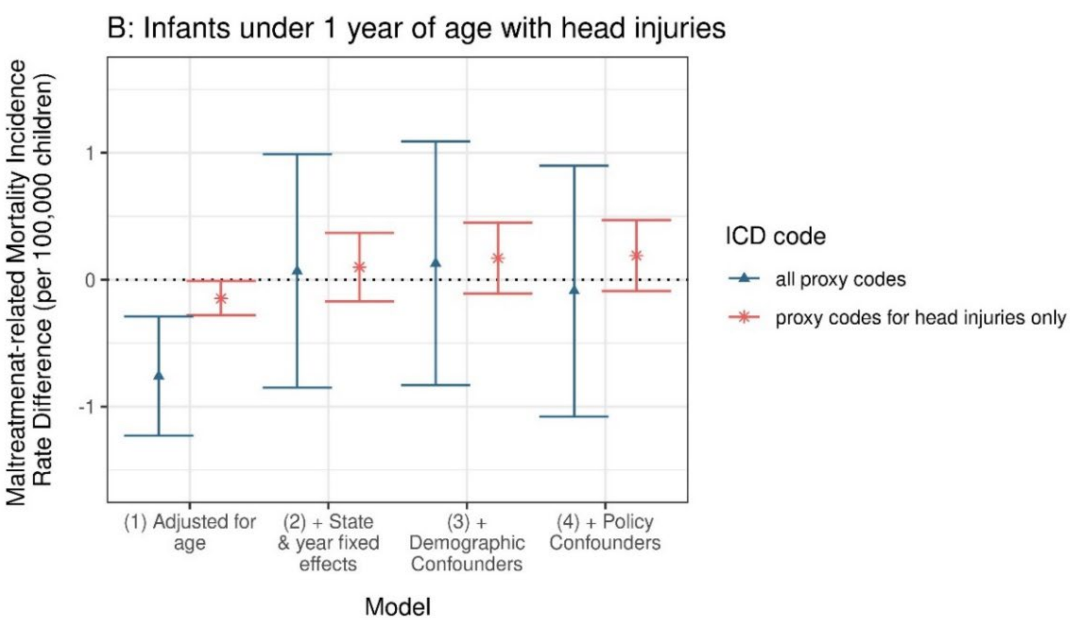
Supplemental Figure 4.7. Results of sensitivity analyses comparing alternate timings of minimum wage changes: incidence rate difference point estimates (per 100,000 children) and 95% confidence intervals for the effect of a $1 increase in minimum wage on child maltreatment-related death rates, stratified by type of ICD code used to identify deaths



Effective minimum wage was calculated using: (1) a weighted average of the effective minimum wage for each year (main model); (2) effective minimum wage as of January 1st of each year, (3) effective minimum wage as of January 1st of the previous year (Delayed 1 Year), and (4) effective minimum wage as of January 1st of the following year (Pre-empted 1 Year)

Supplemental Figure 4.8. Results of sensitivity analyses restricting to infants under 1 year of age: Incidence rate difference point estimates (per 100,000 children) and 95% confidence intervals for the effect of a $1 increase in minimum wage on child maltreatment-related death rates, colored by type of ICD code used to identify deaths, and stratified by inclusion of head injuries (Panel B)





Panel A depicts incidence rate difference point estimates (per 100,000 children) and 95% confidence intervals for the effect of a $1 increase in minimum wage on child maltreatment-related death rates among infants under 1 year of age; Panel B compares effects among all infants under 1 year of age using all proxy codes to the effects of infants under 1 year of age with head injury proxy codes.

Chapter 5: Conclusion

Many prevalent adverse health outcomes in the U.S. are intertwined with poverty and low income. The negative effects of poverty can follow children from birth into adulthood impacting their quality of life, their health, and ultimately their opportunities for economic success. Further, longstanding health disparities by race and ethnicity are exacerbated by structural factors and policies which serve to perpetuate income inequality and make it difficult for some people to achieve upward economic mobility.

Since poverty is a social determinant of health, addressing root causes of poverty through structural interventions is critical for reducing the burden of disease and morality, and for mitigating health disparities. Low income is a risk factor for both food insecurity and child maltreatment, so identifying effective upstream poverty alleviating policies can help to improve the health and nutrition of millions of individuals and potentially prevent thousands of maltreatment-related deaths.

The aim of this dissertation was to build on prior work and contribute to our understanding of how minimum wages impact disparities in child and family health outcomes, specifically with respect to food insecurity and child maltreatment mortality.

In chapter 2, we leveraged data from a large, population-representative dataset to examine the impact of state-level minimum wages on household food insecurity among working-aged U.S. households between 2002 and 2019. While this work found no overall effect of minimum wages on food insecurity, it did uncover important heterogeneity in effect: a $1 increase in minimum wage led to decreases in food insecurity for households whose head has less than a high school diploma, households headed by single women, Indigenous households, and multiracial households (with children), while leading to increases in food insecurity among Black and multiracial households (overall).

Chapter 3 extended the findings from chapter 2 by examining the effect of state-level minimum wages on household food insecurity among households receiving Supplemental Nutrition Assistance Program (SNAP) benefits. While SNAP is the foremost U.S. food and nutrition program aimed at reducing food insecurity, benefit levels are sensitive to changes in household income. Further, administrative burdens associated with program recertification can make it difficult to obtain and retain benefits when income changes, even if households are still eligible. Thus, impacts of changing minimum wages on food insecurity is especially unclear for this population. Using the same population-representative dataset as in chapter 2, we identified households receiving SNAP benefits and linked them across two years, to estimate the effect of a $1 increase in minimum wage on food insecurity within this population. We again found no overall population-level impact, but important heterogeneity in effect for subpopulations defined by race and ethnicity, educational attainment, family structure, and age: for some groups we found protective effects of minimum wages, for others we found no effect, and for yet others we found harmful effects. We concluded that potential interactions between minimum wages and other safety-net programs are complex and likely driving these disparate effects among SNAP recipients.

Finally, in Chapter 4, we evaluated the impact of state-level minimum wages on child maltreatment-related mortality. We identified child maltreatment-related deaths using death certificate data and an innovative approach which combines explicit and proxy ICD codes to overcome limitations in child maltreatment report data. This study found no effect of a $1 increase in minimum wage on child maltreatment mortality rates, though results suggested there may be heterogeneity according to racial-ethnic identity.

Across all studies, we found that state-level minimum wages have important heterogenous effects on food insecurity and child maltreatment mortality outcomes: while they provide some households with much-needed financial resources to improve their health and well-being, their effect is likely complicated by interactions with other targeted safety-net programs, leading some families to experience worse outcomes. In particular, non-Hispanic Black households tended to experience disproportionately negative consequences of increased minimum wages, suggesting that racist policies, practices, and societal patterns which perpetuate discriminatory beliefs through systems of housing, education, employment, health care, and criminal justice continue to persist and potentially counteract protective structural interventions.

Future work should continue to explore these interactive policy effects to further our understanding of which populations may be simultaneously helped or harmed, so that additional safeguards can be put into place for populations likely to suffer negative impacts, and so that health disparities may truly be eliminated.

References

1. Blumenshine P, Egerter S, Barclay CJ, Cubbin C, Braveman PA. Socioeconomic Disparities in Adverse Birth Outcomes: A Systematic Review. *American Journal of Preventive Medicine*. 2010;39(3):263-272. doi:10.1016/j.amepre.2010.05.012
2. Case A, Lubotsky D, Paxson C. Economic Status and Health in Childhood: The Origins of the Gradient. *American Economic Review*. 2002;92(5):1308-1334. doi:10.1257/000282802762024520
3. Engle PL, Black MM. The Effect of Poverty on Child Development and Educational Outcomes. *Annals of the New York Academy of Sciences*. 2008;1136(1):243-256. doi:10.1196/annals.1425.023
4. Ratcliffe C. *Child Poverty and Adult Success*. Urban Institute; 2015.
5. Evans GW, Kim P. Childhood Poverty, Chronic Stress, Self-Regulation, and Coping. *Child Development Perspectives*. 2013;7(1):43-48. doi:10.1111/cdep.12013
6. Steele H, Bate J, Steele M, et al. Adverse Childhood Experiences, Poverty, and Parenting Stress. *Canadian Journal of Behavioural Science / Revue canadienne des sciences du comportement*. 2016;48:32-38. doi:10.1037/cbs0000034
7. Schiller JS, Lucas JW, Peregoy JA. Summary health statistics for U.S. Adults: national health interview survey, 2011. *Vital Health Stat 10*. 2012;(256):1-218.
8. Chetty R, Stepner M, Abraham S, et al. The Association Between Income and Life Expectancy in the United States, 2001-2014. *JAMA*. 2016;315(16):1750-1766. doi:10.1001/jama.2016.4226
9. Wagmiller RL, Adelman RM. *Childhood and Intergenerational Poverty: The Long-Term Consequences of Growing Up Poor*. National Center for Children in Poverty; 2009. https://www.nccp.org/publication/childhood-and-intergenerational-poverty/
10. Chetty R, Hendren N, Kline P, Saez E, Turner N. Is the United States Still a Land of Opportunity? Recent Trends in Intergenerational Mobility. *American Economic Review*. 2014;104(5):141-147. doi:10.1257/aer.104.5.141
11. Poverty Rate by Race/Ethnicity. Kaiser Family Foundation. Accessed April 23, 2024. https://www.kff.org/other/state-indicator/poverty-rate-by-raceethnicity/
12. Creamer J. Inequalities Persist Despite Decline in Poverty For All Major Race and Hispanic Origin Groups. United States Census Bureau. Published September 15, 2020. https://www.census.gov/library/stories/2020/09/poverty-rates-for-blacks-and-hispanics-reached-historic-lows-in-2019.html
13. Dubay LC, Lebrun LA. Health, Behavior, and Health Care Disparities: Disentangling the Effects of Income and Race in the United States. *Int J Health Serv*. 2012;42(4):607-625. doi:10.2190/HS.42.4.c

14. Williams DR. Race, Socioeconomic Status, and Health The Added Effects of Racism and Discrimination. *Annals of the New York Academy of Sciences*. 1999;896(1):173-188. doi:10.1111/j.1749-6632.1999.tb08114.x

15. Kawachi I, Adler NE, Dow WH. Money, schooling, and health: Mechanisms and causal evidence. *Annals of the New York Academy of Sciences*. 2010;1186(1):56-68. doi:10.1111/j.1749-6632.2009.05340.x

16. Liu Y, Croft JB, Chapman DP, et al. Relationship between adverse childhood experiences and unemployment among adults from five U.S. states. *Soc Psychiatry Psychiatr Epidemiol*. 2013;48(3):357-369. doi:10.1007/s00127-012-0554-1

17. Ross M, Bateman N. *Meet the Low-Wage Workforce*. Metropolitan Policy Program at Brookings; 2019. Accessed April 20, 2024. https://www.brookings.edu/articles/meet-the-low-wage-workforce/

18. Hoynes HW, Page ME, Stevens AH. Poverty in America: Trends and Explanations. *Journal of Economic Perspectives*. 2006;20(1):47-68. doi:10.1257/089533006776526102

19. History of Federal Minimum Wage Rates Under the Fair Labor Standards Act, 1938 - 2009. US Department of Labor. Accessed April 23, 2024. https://www.dol.gov/agencies/whd/minimum-wage/history/chart

20. Inventory of US City and County Minimum Wage Ordinances. UC Berkeley Labor Center. Accessed March 1, 2024. https://laborcenter.berkeley.edu/inventory-of-us-city-and-county-minimum-wage-ordinances/

21. Minimum Wage Tracker. Economic Policy Institute. Published March 1, 2024. Accessed April 2, 2021. https://www.epi.org/minimum-wage-tracker/

22. Dube A. *Impacts of Minimum Wages: Review of the International Evidence*. University of Massachusetts Amherst, National Bureau of Economic Research and IZA Institute of Labor Economics; 2019. www.gov.uk/government/publications

23. Dube A. Minimum Wages and the Distribution of Family Incomes. *American Economic Journal: Applied Economics*. 2019;11(4):268-304. doi:10.1257/app.20170085

24. Cengiz D, Dube A, Lindner A, Zipperer B. *The Effect of Minimum Wages on Low-Wage Jobs: Evidence from the United States Using a Bunching Estimator*. National Bureau of Economic Research; 2019:w25434. doi:10.3386/w25434

25. Neumark D. The Effects of Minimum Wages on (Almost) Everything? A Review of Recent Evidence on Health and Related Behaviors. Published online April 2023. doi:10.3386/w31191

26. Callaway B, Sant'Anna PHC. Difference-in-Differences with multiple time periods. *Journal of Econometrics*. 2021;225(2):200-230. doi:10.1016/j.jeconom.2020.12.001

27. Goodman-Bacon A. Difference-in-differences with variation in treatment timing. *Journal of Econometrics*. 2021;225(2):254-277. doi:10.1016/j.jeconom.2021.03.014

28. Borusyak K, Jaravel X, Spiess J. Revisiting Event-Study Designs: Robust and Efficient Estimation. *The Review of Economic Studies*. Published online February 6, 2024:rdae007. doi:10.1093/restud/rdae007

29. De Chaisemartin C, D'Haultfœuille X. Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *American Economic Review*. 2020;110(9):2964-2996. doi:10.1257/aer.20181169

30. Sun L, Abraham S. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*. 2021;225(2):175-199. doi:10.1016/j.jeconom.2020.09.006

31. Hales LJ, Coleman-Jensen A. Food Security in the U.S.: Interactive Charts and Highlights. USDA Economic Research Service. Published October 2023. https://www.ers.usda.gov/topics/food-nutrition-assistance/food-security-in-the-u-s/interactive-charts-and-highlights/

32. Hartline-Grafton H. *The Role of the Supplemental Nutrition Assistance Program (SNAP) in Improving Health and Well-Being*. Food Research and Action Center; 2017:24. https://frac.org/research/resource-library/snap-public-health-role-supplemental-nutrition-assistance-program-improving-health-well%e2%80%90being-americans

33. Rabbitt MP, Hales LJ, Burke MP, Coleman-Jensen A. *Household Food Security in the United States in 2022*. U.S. Department of Agriculture, Economic Research Service.; 2023. https://doi.org/10.32747/2023.8134351.ers

34. Gundersen C, Kreider B, Pepper J. The Economics of Food Insecurity in the United States. *Applied Economic Perspectives and Policy*. 2011;33(3):281-303. doi:10.1093/aepp/ppr022

35. Mabli J, Worthington J. Supplemental Nutrition Assistance Program Participation and Child Food Security. *Pediatrics*. 2014;133(4):610-619. doi:10.1542/peds.2013-2823

36. Mabli J, Ohls J. Supplemental Nutrition Assistance Program Participation Is Associated with an Increase in Household Food Security in a National Evaluation. *The Journal of Nutrition*. 2015;145(2):344-351. doi:10.3945/jn.114.198697

37. Mykerezi E, Mills B. The Impact of Food Stamp Program Participation on Household Food Insecurity. *American Journal of Agricultural Economics*. 2010;92(5):1379-1391. doi:10.1093/ajae/aaq072

38. Ratcliffe C, McKernan SM, Zhang S. How Much Does the Supplemental Nutrition Assistance Program Reduce Food Insecurity? *Am J Agric Econ*. 2011;93(4):1082-1098. doi:10.1093/ajae/aar026

39. Shaefer HL, Gutierrez IA. The Supplemental Nutrition Assistance Program and Material Hardships among Low-Income Households with Children. *Social Service Review*. 2013;87(4):753-779. doi:10.1086/673999

40. Bronchetti ET, Christensen G, Hoynes HW. Local food prices, SNAP purchasing power, and child health. *Journal of Health Economics*. 2019;68:102231. doi:10.1016/j.jhealeco.2019.102231

41. *SNAP Matters: How Food Stamps Affect Health and Well-Being*. Stanford University Press; 2015.

42. Hoynes H, Schanzenbach DW, Almond D. Long-Run Impacts of Childhood Access to the Safety Net. *American Economic Review*. 2016;106(4):903-934. doi:10.1257/aer.20130375

43. Sandel M, Cutts D, Meyers A, et al. Co-enrollment for Child Health: How Receipt and Loss of Food and Housing Subsidies Relate to Housing Security and Statutes for Streamlined, Multi-Subsidy Application. *Journal of Applied Research on Children: Informing Policy for Children at Risk*. 2015;5(2). doi:10.58464/2155-5834.1214

44. Tiehen L, Jolliffe D, Gundersen C. *Alleviating Poverty in the United States: The Critical Role of SNAP Benefits*. USDA Economic Research Service; 2012.

45. Edin K, Melody Boyd, James Mabli, et al. *SNAP Food Security In-Depth Interview Study*. U.S. Department of Agriculture, Food and Nutrition Service, Office of Research and Analysis.; 2013.

46. Gosliner W, Shah H. Participant voices: examining issue, program and policy priorities of SNAP-Ed eligible adults in California. *Renew Agric Food Syst*. 2020;35(4):407-415. doi:10.1017/S1742170519000243

47. Carlson S, Keith-Jennings B, Llobrera J. *Policy Brief: Modernizing SNAP Benefits Would Help Millions Better Afford Healthy Food*. Center on Budget and Policy Priorities; 2021. https://www.cbpp.org/research/food-assistance/modernizing-snap-benefits-would-help-millions-better-afford-healthy-food

48. Daponte BO. Linking SNAP to Food Security: Exploring Reinstating a Purchase Requirement and Tying Benefits to the Low-Cost Food Plan. *The Economists' Voice*. 2017;14(1). doi:10.1515/ev-2017-0007

49. Gearing M, Dixit-Joshi S, Whitsel L. *Barriers That Constrain the Adequacy of Supplemental Nutrition Assistance Program (SNAP) Allotments: Survey Findings.* USDA Food and Nutrition Service; 2021. Accessed April 23, 2024. https://www.fns.usda.gov/snap/barriers-constrain-adequacy-snap-allotments

50. Coleman-Jensen A. Household Food Security in the United States in 2019. Published online 2019:47.

51. Children's Bureau, Administration on Children, Youth and Families, Administration for Children and Families, U. S. Department of Health and Human Services. National Child Abuse and Neglect Data System (NCANDS) Child File, FY 2000- FY2019 [Dataset]. doi:10.34681/04hy-mc45

52. Schnitzer PG, Gulino SP, Yuan YYT. Advancing public health surveillance to estimate child maltreatment fatalities: review and recommendations. *Child Welfare*. 2013;92(2):77-98.

53. Dettlaff AJ, Boyd R. Racial Disproportionality and Disparities in the Child Welfare System: Why Do They Exist, and What Can Be Done to Address Them? *The ANNALS of the American Academy of Political and Social Science*. 2020;692(1):253-274. doi:10.1177/0002716220980329

54. Thomas MMC, Waldfogel J, Williams OF. Inequities in Child Protective Services Contact Between Black and White Children. *Child Maltreat*. 2023;28(1):42-54. doi:10.1177/10775595211070248

55. Harris MS, Hackett W. Decision points in child welfare: An action research model to address disproportionality. *Children and Youth Services Review*. 2008;30(2):199-215. doi:10.1016/j.childyouth.2007.09.006

56. Hill RB. *An Analysis Of Racial/Ethnic Disproportionality and Disparity at the National, State, and County Levels*. Casey Family Programs; 2007.

57. Cort NA, Cerulli C, He H. Investigating Health Disparities and Disproportionality in Child Maltreatment Reporting: 2002–2006. *Journal of Public Health Management and Practice*. 2010;16(4):329. doi:10.1097/PHH.0b013e3181c4d933

58. Sedlak AJ, Mettenburg J, Basena M, et al. Fourth National Incidence Study of Child Abuse and Neglect (NIS–4).

59. Berger LM. Income, family structure, and child maltreatment risk. *Children and Youth Services Review*. 2004;26(8):725-748. doi:10.1016/j.childyouth.2004.02.017

60. Coulton CJ, Crampton DS, Irwin M, Spilsbury JC, Korbin JE. How neighborhoods influence child maltreatment: A review of the literature and alternative pathways. *Child Abuse & Neglect*. 2007;31(11-12):1117-1142. doi:10.1016/j.chiabu.2007.03.023

61. Berger LM, Font SA, Slack KS, Waldfogel J. Income and child maltreatment in unmarried families: evidence from the earned income tax credit. *Rev Econ Household*. 2017;15(4):1345-1372. doi:10.1007/s11150-016-9346-9

62. Cancian M, Yang MY, Slack KS. The Effect of Additional Child Support Income on the Risk of Child Maltreatment. *Social Service Review*. 2013;87(3):417-437. doi:10.1086/671929

63. Raissian KM, Bullinger LR. Money matters: Does the minimum wage affect child maltreatment rates? *Children and Youth Services Review*. 2017;72:60-70. doi:10.1016/j.childyouth.2016.09.033

64. Livingston MD, Woods-Jaeger B, Spencer RA, Lemon E, Walker A, Komro KA. Association of State Minimum Wage Increases with Child Maltreatment. *J Interpers Violence*. 2022;37(21-22):NP21411-NP21421. doi:10.1177/08862605211056727

65. Ash MJ, Livingston MD, Komro K, Spencer RA, Walker A, Woods-Jaeger B. The Impact of Increased Minimum Wage on Child Neglect Varies by Developmental Age of Child. *J Interpers Violence*. Published online January 30, 2023:088626052211504. doi:10.1177/08862605221150458

66. Janio EA, Sorkin DH. Food insecurity and healthcare access, utilization, and quality among middle and later life adults in California. *J Aging Health*. 2021;33(3-4):171-186. doi:10.1177/0898264320967563

67. Berkowitz SA, Basu S, Meigs JB, Seligman HK. Food Insecurity and Health Care Expenditures in the United States, 2011–2013. *Health Services Research*. Published online 2018:21. doi:10.1111/1475-6773.12730

68. Jones JW, Toossi S. U.S. Food and Nutrition Assistance Programs Continued To Respond to Economic and Public Health Conditions in Fiscal Year 2022. USDA Economic Research Service. Accessed February 21, 2024. https://www.ers.usda.gov/amber-waves/2023/august/u-s-food-and-nutrition-assistance-programs-continued-to-respond-to-economic-and-public-health-conditions-in-fiscal-year-2022/

69. Clemens J. How Do Firms Respond to Minimum Wage Increases? Understanding the Relevance of Non-employment Margins. *Journal of Economic Perspectives*. 2021;35(1):51-72. doi:10.1257/jep.35.1.51

70. Sherk J. *$15 Minimum Wages Will Substantially Raise Prices*. The Heritage Foundation; 2017. Accessed April 18, 2024. http://report.heritage.org/bg3160

71. Beck L, Quinn EL, Hill HD, Wolf J, Buszkiewicz J, Otten JJ. Low-income workers' perceptions of wages, food acquisition, and well-being. *Transl Behav Med*. 2019;9(5):942-951. doi:10.1093/tbm/ibz113

72. Caspi CE, De Marco M, Welle E, et al. A qualitative analysis of SNAP and minimum wage policies as experienced by workers with lower incomes. *J Hunger Environ Nutr*. 2022;17(4):521-539. doi:10.1080/19320248.2021.1997859

73. Sabia JJ, Nielsen RB. Minimum wages, poverty, and material hardship: new evidence from the SIPP. *Rev Econ Household*. 2015;13(1):95-134. doi:10.1007/s11150-012-9171-8

74. Caspi CE, Gombi-Vaca MF, Wolfson J, et al. Early results of a natural experiment evaluating the effects of a local minimum wage policy on the diet-related health of low-wage workers, 2018–2020. *Public Health Nutr*. 26(11):2573-2585. doi:10.1017/S1368980023001520

75. Heflin CM. The Importance of Context to the Social Processes Around Material Hardship. In: *The Routledge Handbook of Poverty in the United States*. Routledge Press; 2015:120-129. https://ebookcentral-proquest-com.libproxy.berkeley.edu/lib/berkeley-ebooks/detail.action?docID=1899868.

76. Chapman LE, Berkowitz SA, Ammerman A, et al. Examining Changes in Food Security, Perceived Stress, and Dietary Intake in a Cohort of Low-Wage Workers Experiencing an Increase in Hourly Wage. *Health Promotion Practice*. Published online November 14, 2022:15248399221128005. doi:10.1177/15248399221128005

77. Coleman-Jensen A, Rabbitt MP, Gregory CA, Singh A. *Statistical Supplement to Household Food Security in the United States in 2019*. Economic Research Service, U.S. Department of Agriculture; 2020. doi:10.32747/2023.8134352.ers

78. Walker RJ, Garacci E, Dawson AZ, Williams JS, Ozieh M, Egede LE. Trends in Food Insecurity in the United States from 2011–2017: Disparities by Age, Sex, Race/Ethnicity, and Income. *Population Health Management*. 2021;24(4):496-501. doi:10.1089/pop.2020.0123

79. Coleman-Jensen A, Nord M, Andrews M, Carlson S. *Household Food Security in the United States in 2010*. Economic Research Service, USDA; 2010.

80. Current Population Survey. U.S. Bureau of Labor Statistics. Published January 24, 2023. Accessed March 18, 2024. https://www.bls.gov/cex/cecomparison/cps_profile.htm

81. Flood S, King M, Rodgers R, Ruggles S, Warren JR, Westberry M. *Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [2009-2019]*. IPUMS, 2022 Accessed March 2, 2023. https://doi.org/10.18128/D030.V9.0

82. Niles MT, Beavers AW, Clay LA, et al. A Multi-Site Analysis of the Prevalence of Food Insecurity in the United States, before and during the COVID-19 Pandemic. *Current Developments in Nutrition*. 2021;5(12):nzab135. doi:10.1093/cdn/nzab135

83. Coleman-Jensen A, Rabbitt MP, Hales L, Gregory CA. Definitions of Food Security. Economic Research Service (ERS), U.S. Department of Agriculture (USDA). Accessed August 2, 2023. https://www.ers.usda.gov/topics/food-nutrition-assistance/food-security-in-the-u-s/definitions-of-food-security/

84. Coleman-Jensen AJ. U.S. Food Insecurity Status: Toward a Refined Definition. *Soc Indic Res*. 2010;95(2):215-230. doi:10.1007/s11205-009-9455-4

85. University of Kentucky Center for Poverty Research. UKCPR National Welfare Data, 1980-2020. Published online 2022. http://ukcpr.org/resources/national-welfare-data

86. U.S. Department of Labor. Questions and Answers About the Minimum Wage. Wage and Hour Division. Accessed March 8, 2023. http://www.dol.gov/agencies/whd/minimum-wage/faq

87. U.S. Bureau of Labor Statistics. Consumer Price Index for All Urban Consumers: All Items in U.S. City Average [CPIAUCSL], retrieved from FRED. Federal Reserve Bank of St. Louis. Published March 8, 2023. Accessed February 27, 2023. https://fred.stlouisfed.org/series/CPIAUCSL

88. Timoneda JC. Estimating group fixed effects in panel data with a binary dependent variable: How the LPM outperforms logistic regression in rare events data. *Social Science Research*. 2021;93:102486. doi:10.1016/j.ssresearch.2020.102486

89. Wooldridge JM. *Econometric Analysis of Cross Section and Panel Data*. The MIT Press

90. Gundersen C, Waxman E, Engelhard E, Satoh A, Chawla N. *Map the Meal Gap 2013: Technical Brief*.

91. Tapogna J, Suter A, Nord M, Leachman M. Explaining variations in state hunger rates. *Family and Economics Nutrition Review,*. 2004;16(2):12-22.

92. Bartfeld J, Dunifon R, Nord M, Carlson S. What Factors Account for State-to-State Differences in Food Security? *Economic Information Bulletin*. Published online 2006. Accessed January 29, 2023. https://ideas.repec.org//p/ags/uersib/7086.html

93. Bartfeld J, Dunifon R. State-level predictors of food insecurity among households with children. *Journal of Policy Analysis and Management*. 2006;25(4):921-942. doi:10.1002/pam.20214

94. Gundersen C, Gruber J. The dynamic determinants of food insufficiency. In: M.S. Andrews & M.A. Prell (Eds.), Second Food Security Measurement and Research Conference, Volume II: Papers. (Food Assistance and Nutrition Research Report No. 11-2, pp. 91-109). U.S. Department of Agriculture, Economic Research Service; 2001.

95. U.S. Department of Housing and Urban Development. 50th Percentile Rent Estimates: Data by Area 2009-2019. Published online May 29, 2023. Accessed May 29, 2023. https://www.huduser.gov/portal/datasets/50per.html

96. Mathematica. *Reaching Those in Need: Estimates of State Supplemental Nutrition Assistance Program Participation Rates*. U.S. Department of Agriculture, Food and Nutrition Service.

97. Fox A. State Safety-net Generosity Index. Published 2021. Accessed March 22, 2023. https://safetynetgenerosity.com/

98. State Law Information, Employment & Training Administration. U.S. Department of Labor. Published February 1, 2023. Accessed March 24, 2023. https://oui.doleta.gov/unemploy/statelaws.asp

99. Solon G, Haider SJ, Wooldridge JM. What are we weighting for? *National Bureau of Economic Research*. 2013;(Working Paper 18859). http://www.nber.org/papers/w18859

100. Korn EL, Graubard BI. *Analysis of Health Surveys*. Jon Wiley & Sons Inc.; 1999.

101. Bollen KA, Biemer PP, Karr AF, Tueller S, Berzofsky ME. Are Survey Weights Needed? A Review of Diagnostic Tests in Regression Analysis. *Annual Review of Statistics and Its Application*. 2016;3(1):375-392. doi:10.1146/annurev-statistics-011516-012958

102. Tools of the trade: when to use those sample weights. World Bank Blogs. Accessed March 30, 2024. https://blogs.worldbank.org/en/impactevaluations/tools-of-the-trade-when-to-use-those-sample-weights

103. Schempf AH, Kaufman JS. Accounting for context in studies of health inequalities: a review and comparison of analytic approaches. *Annals of Epidemiology*. 2012;22(10):683-690. doi:10.1016/j.annepidem.2012.06.105

104. Even WE, Macpherson DA. The Effect of the Tipped Minimum Wage on Employees in the U.S. Restaurant Industry. *Southern Economic Journal*. 2014;80(3):633-655.

105. Parolin Z. Temporary Assistance for Needy Families and the Black–White child poverty gap in the United States. *Socio-Economic Review*. 2021;19(3):1005-1035. doi:10.1093/ser/mwz025

106. Ray V, Herd P, Moynihan D. Racialized Burdens: Applying Racialized Organization Theory to the Administrative State. *Journal of Public Administration Research and Theory*. 2023;33(1):139-152. doi:10.1093/jopart/muac001

107. Pratt E, Hahn H. *What Happens When People Face Unfair Treatment or Judgment When Applying for Public Assistance or Social Services?* Urban Institute; 2021.

108. Rank MR, Hirschl TA. Estimating the Risk of Food Stamp Use and Impoverishment During Childhood. *Archives of Pediatrics & Adolescent Medicine*. 2009;163(11):994-999. doi:10.1001/archpediatrics.2009.178

109. Prior HHS Poverty Guidelines and Federal Register References. Office of the Assistant Secretary for Planning and Evaluation. Published 2024. Accessed March 30, 2024. https://aspe.hhs.gov/topics/poverty-economic-mobility/poverty-guidelines/prior-hhs-poverty-guidelines-federal-register-references

110. A closer look at low-wage workers across the country. Brookings. Accessed March 19, 2024. https://www.brookings.edu/articles/low-wage-workforce/

111. World Health Organization. A conceptual framework for action on the social determinants of health. Published online 2010:76.

112. Schroeder K, Smaldone A. Food insecurity: A concept analysis. *Nurs Forum*. 2015;50(4):274-284. doi:10.1111/nuf.12118

113. Torpey E. Same occupation, different pay: How wages vary. U.S. Bureau of Labor Statistics. Published May 2015. Accessed March 31, 2024. https://www.bls.gov/careeroutlook/2015/article/wage-differences.htm

114. Hagenaars AJM, ed. Chapter 3 - Determinants of Income. In: *The Perception of Poverty*. Vol 156. Contributions to Economic Analysis. Elsevier; 1986:67-85. doi:10.1016/B978-0-444-87898-4.50010-X

115. US Department of Agriculture. SNAP Data Tables. USDA Food and Nutrition Service. Published 2024. https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap

116. US Department of Agriculture. SNAP Eligibility. USDA Food and Nutrition Service. Published 2024. https://www.fns.usda.gov/snap/recipient/eligibility

117. Gundersen C, Ziliak JP. Food Insecurity And Health Outcomes. *Health Affairs*. 2015;34(11):1830-1839. doi:10.1377/hlthaff.2015.0645

118. Policy Basics: The Supplemental Nutrition Assistance Program (SNAP). Center on Budget and Policy Priorities. Published June 9, 2022. Accessed March 28, 2024. https://www.cbpp.org/research/policy-basics-the-supplemental-nutrition-assistance-program-snap

119. *SNAP Recertification Toolkit*. USDA Food and Nutrition Service; 2018.

120. Homonoff T, Somerville J. Program Recertification Costs: Evidence from SNAP. In: NBER Working Paper Series 27311. National Bureau of Economic Research; 2020. http://www.nber.org/papers/w27311

121. SNAP COVID-19 Emergency Allotments Guidance. USDA Food and Nutrition Service. Published 2023. Accessed March 28, 2024. https://www.fns.usda.gov/snap/covid-19-emergency-allotments-guidance

122. Himmelstein G. Effect of the Affordable Care Act's Medicaid Expansions on Food Security, 2010–2016. *Am J Public Health*. 2019;109(9):1243-1248. doi:10.2105/AJPH.2019.305168

123. Londhe S, Ritter G, Schlesinger M. Medicaid Expansion in Social Context: Examining Relationships Between Medicaid Enrollment and County-Level Food Insecurity. *Journal of Health Care for the Poor and Underserved*. 2019;30(2):532-546.

124. Kalton G, Flores-Cervantes I. Weighting methods. *Journal of Official Statistics*. 2003;19(2):81-97.

125. Hoynes H. The Earned Income Tax Credit. *The ANNALS of the American Academy of Political and Social Science*. 2019;686(1):180-203. doi:10.1177/0002716219881621

126. Curran MA. *Research Roundup of the Expanded Child Tax Credit: The First 6 Months*. Center on Poverty and Social Policy at Columbia University; 2021.

127. Currie J. *The Invisible Safety Net: Protecting the Nation's Poor Children and Families*. Princeton University Press; 2008. Accessed April 11, 2024. https://press.princeton.edu/books/paperback/9780691138527/the-invisible-safety-net

128. Hartline-Grafton H. *School Meals Are Essential for Student Health and Learning*. Food Research and Action Center; 2021.

129. Fry R, Braga D. The growth of the older workforce. Pew Research Center's Social & Demographic Trends Project. Published December 14, 2023. Accessed April 4, 2024. https://www.pewresearch.org/social-trends/2023/12/14/the-growth-of-the-older-workforce/

130. Primus W, Paris J. Seven facts about the economic security of older adults. Brookings. Published December 6, 2023. Accessed April 4, 2024. https://www.brookings.edu/articles/seven-facts-about-the-economic-security-of-older-adults/

131. Low wage worker distribution by age U.S. 2022. Statista. Accessed March 18, 2024. https://www.statista.com/statistics/298866/percentage-of-low-wage-workers-in-the-us-by-age/

132. Hampton M, Totty E. Minimum wages, retirement timing, and labor supply. *Journal of Public Economics*. 2023;224(104924). doi:10.1016/j.jpubeco.2023.104924

133. Sabia JJ, Burkhauser RV. Minimum Wages and Poverty: Will a $9.50 Federal Minimum Wage Really Help the Working Poor? *Southern Economic Journal*. 2010;76(3):592-623.

134. Johnson RW, Favreault MM, Dey J, Marton W, Anderson L. *Risk of Economic Hardship Among Older Adults Issue Brief*. Office of the Assitant Secretary for Planning and Evaluation (ASPE); 2021. Accessed April 23, 2024. https://aspe.hhs.gov/reports/risk-economic-hardship-among-older-adults-issue-brief-0

135. What isn't covered by Part A & Part B? Medicare.gov. Accessed April 21, 2024. https://www.medicare.gov/what-medicare-covers/what-isnt-covered-by-part-a-part-b

136. Medicare eligibility for those 65+. Medicare Interactive. Accessed April 21, 2024. https://www.medicareinteractive.org/get-answers/medicare-basics/medicare-eligibility-overview/medicare-eligibility-for-those-65

137. U.S. Bureau of Labor Statistics. Characteristics of minimum wage workers, 2019. "Characteristics of Minimum Wage Workers, 2020. Published April 2020. Accessed April 4, 2024. https://www.bls.gov/opub/reports/minimum-wage/2019/home.htm

138. Herd P, Hoynes H, Michener J, Moynihan D. Introduction: Administrative Burden as a Mechanism of Inequality in Policy Implementation. *RSF: The Russell Sage Foundation Journal of the Social Sciences*. 2023;9(5):1-30. doi:10.7758/RSF.2023.9.5.01

139. Johnson J, Rochkind J. *With Their Whole Lives Ahead of Them: Myths and Realities about Why So Many Students Fail to Finish College*. Public Agenda; 2009. Accessed April 4, 2024. https://eric.ed.gov/?id=ED507432

140. Zipperer B, McNicholas C, Poydock M, Schneider D, Harknett K. National survey of gig workers paints a picture of poor working conditions, low pay. Economic Policy Institute. Published June 1, 2022. Accessed April 4, 2024. https://www.epi.org/publication/gig-worker-survey/

141. Grall T. *Custodial Mothers and Fathers and Their Child Support: 2017*. United States Census Bureau; 2020.

142. Shipe SL, Ayer L, Guastaferro K. American Single Father Homes: A Growing Public Health Priority. *Am J Public Health*. 2022;112(1):21-23. doi:10.2105/AJPH.2021.306591

143. Hahn H. Why fathers often don't apply for cash assistance. Urban Institute. Published June 23, 2016. Accessed April 4, 2024. https://www.urban.org/urban-wire/why-fathers-often-dont-apply-cash-assistance

144. Characteristics of SNAP Households: FY 2019. USDA Food and Nutrition Service. Published December 13, 2023. Accessed April 11, 2024. https://www.fns.usda.gov/snap/characteristics-snap-households-fy-2019

145. Cooper D, Martinez Hickey S, Zipperer B. The value of the federal minimum wage is at its lowest point in 66 years. Economic Policy Institute, Working Economics Blog. Published July 14, 2022. Accessed April 11, 2024. https://www.epi.org/blog/the-value-of-the-federal-minimum-wage-is-at-its-lowest-point-in-66-years/

146. Wheaton L. Underreporting of Means-Tested Transfer Programs in the CPS and SIPP.

147. Meyer BD, Mittag N, Goerge RM. Errors in Survey Reporting and Imputation and Their Effects on Estimates of Food Stamp Program Participation. *J Human Resources*. 2022;57(5):1605-1644. doi:10.3368/jhr.58.1.0818-9704R2

148. Cost of Living Data Series. Missouri Economic Research and Information Center. Accessed April 22, 2024. https://meric.mo.gov/data/cost-living-data-series

149. Schmidt L, Shore-Sheppard L, Watson T. State Safety Net Database version 1.1 [dataset]. Brookings Institution, Washington, D.C. Published online November 28, 2023. https://www.brookings.edu/articles/state-safety-net-interactive/

150. Sedlak AJ, Mettenburg J, Basena M, et al. Fourth national incidence study of child abuse and neglect (NIS-4). *Washington, DC: US Department of Health and Human Services*. 2010;9:2010.

151. Berger LM. Income, family structure, and child maltreatment risk. *Children and Youth Services Review*. 2004;26(8):725-748. doi:10.1016/j.childyouth.2004.02.017

152. Berger LM, Font SA, Slack KS, Waldfogel J. Income and Child Maltreatment in Unmarried Families: Evidence from the Earned Income Tax Credit. *Rev Econ Househ*. 2017;15(4):1345-1372. doi:10.1007/s11150-016-9346-9

153. Cancian M, Yang MY, Slack KS. The Effect of Additional Child Support Income on the Risk of Child Maltreatment. *Social Service Review*. 2013;87(3):417-437. doi:10.1086/671929

154. Pelton LH. The continuing role of material factors in child maltreatment and placement. *Child Abuse & Neglect*. 2015;41:30-39. doi:10.1016/j.chiabu.2014.08.001

155. Child Welfare Information Gateway. Definitions of child abuse and neglect. U.S. Department of Health and Human Services, Administration for Children and Families, Children’s Bureau. Published 2022. Accessed April 14, 2023. https://www.childwelfare.gov/pubpdfs/define.pdf

156. Belsky J. The determinants of parenting: a process model. *Child Dev*. 1984;55(1):83-96. doi:10.1111/j.1467-8624.1984.tb00275.x

157. Hill. *Families under Stress: Adjustment to the Crises of War Separation and Reunion*. Harper & Brothers; 1949.

158. Masarik AS, Conger RD. Stress and child development: a review of the Family Stress Model. *Current Opinion in Psychology*. 2017;13:85-90. doi:10.1016/j.copsyc.2016.05.008

159. Raio CM, Orederu TA, Palazzolo L, Shurick AA, Phelps EA. Cognitive emotion regulation fails the stress test. *Proc Natl Acad Sci U S A*. 2013;110(37):15139-15144. doi:10.1073/pnas.1305706110

160. Zhan J, Wu X, Fan J, et al. Regulating Anger under Stress via Cognitive Reappraisal and Sadness. *Frontiers in Psychology*. 2017;8. Accessed May 31, 2023. https://www.frontiersin.org/articles/10.3389/fpsyg.2017.01372

161. Raissian KM, Bullinger LR. Money matters: Does the minimum wage affect child maltreatment rates? *Children and Youth Services Review*. 2017;72:60-70. doi:10.1016/j.childyouth.2016.09.033

162. Livingston MD, Woods-Jaeger B, Spencer RA, Lemon E, Walker A, Komro KA. Association of State Minimum Wage Increases with Child Maltreatment. *J Interpers Violence*. 2022;37(21-22):NP21411-NP21421. doi:10.1177/08862605211056727

163. *Child Maltreatment 2021*. U.S. Department of Health & Human Services Administration for Children and Families Administration on Children, Youth and Families Children's Bureau; 2022. https://www.acf.hhs.gov/cb/data-research/child-maltreatment

164. Schnitzer PG, Gulino SP, Yuan YYT. Advancing public health surveillance to estimate child maltreatment fatalities: review and recommendations. *Child Welfare*. 2013;92(2):77-98.

165. Sell K, Zlotnik S, Noonan K, Rubin D. *The Recession and Child Maltreatment*.; 2010.

166. Stephens-Davidowitz S. Unreported Victims of an Economic Downturn. *Retrieved from Seth Stephens-Davidowitz website*. Published online July 6, 2013:36.

167. World Health Organization. International Classification of Diseases (ICD) : Cause of death. Accessed March 8, 2023. https://www.who.int/standards/classifications/classification-of-diseases/cause-of-death

168. Rovi S, Johnson MS. Physician use of diagnostic codes for child and adult abuse. *J Am Med Womens Assoc (1972)*. 1999;54(4):211-214.

169. Ewigman B, Kivlahan C, Land G. The Missouri child fatality study: underreporting of maltreatment fatalities among children younger than five years of age, 1983 through 1986. *Pediatrics*. 1993;91(2):330-337.

170. Herman-Giddens ME, Brown G, Verbiest S, et al. Underascertainment of child abuse mortality in the United States. *JAMA*. 1999;282(5):463-467. doi:10.1001/jama.282.5.463

171. Schnitzer PG, Covington TM, Wirtz SJ, Verhoek-Oftedahl W, Palusci VJ. Public Health Surveillance of Fatal Child Maltreatment: Analysis of 3 State Programs. *Am J Public Health*. 2008;98(2):296-303. doi:10.2105/AJPH.2006.087783

172. Keenan HT, Campbell KA, Page K, Cook LJ, Bardsley T, Olson LM. Perceived social risk in medical decision-making for physical child abuse: a mixed-methods study. *BMC Pediatrics*. 2017;17(1):214. doi:10.1186/s12887-017-0969-7

173. Thyen U, Leventhal JM, Yazdgerdi SR, Perrin JM. Concerns about child maltreatment in hospitalized children. *Child Abuse Negl*. 1997;21(2):187-198. doi:10.1016/s0145-2134(96)00144-5

174. Rovi S, Johnson MS. More harm than good? Diagnostic codes for child and adult abuse. *Violence Vict*. 2003;18(5):491-502. doi:10.1891/vivi.2003.18.5.491

175. Peterson L. Child Injury and Abuse-Neglect: Common Etiologies, Challenges, and Courses toward Prevention. *Current Directions in Psychological Science*. 1994;3(4):116-120.

176. Schnitzer PG, Slusher PL, Kruse RL, Tarleton MM. Identification of ICD codes suggestive of child maltreatment. *Child Abuse Negl*. 2011;35(1):3-17. doi:10.1016/j.chiabu.2010.06.008

177. King AJ, Farst KJ, Jaeger MW, Onukwube JI, Robbins JM. Maltreatment-Related Emergency Department Visits Among Children 0 to 3 Years Old in the United States. *Child Maltreat*. 2015;20(3):151-161. doi:10.1177/1077559514567176

178. Rebbe R, Sattler KM, Mienko JA. The Association of Race, Ethnicity, and Poverty With Child Maltreatment Reporting. *Pediatrics*. 2022;150(2):e2021053346. doi:10.1542/peds.2021-053346

179. Santaularia NJ, Ramirez MR, Osypuk TL, Mason SM. Measuring the hidden burden of violence: use of explicit and proxy codes in Minnesota injury hospitalizations, 2004–2014. *Inj Epidemiol*. 2021;8(1):63. doi:10.1186/s40621-021-00354-6

180. National Center for Health Statistics. Detailed Multiple Cause of Death Research Files (2000-2019), as compiled from data provided by the 57 vital statistics jurisdictions through the Vital Statistics Cooperative Program. https://www.cdc.gov/nchs/nvss/nvss-restricted-data.htm

181. Surveillance, Epidemiology, and End Results (SEER) Program. U.S. county-level population files – 19 Age Groups: all states combined (adjusted),1990-2020 4 Expanded Races by Origin. National Cancer Institute. Published February 2022. Accessed March 8, 2023. https://seer.cancer.gov/popdata/download.html

182. US Census Bureau. American Community Survey (ACS). Census.gov. Accessed April 23, 2022. https://www.census.gov/programs-surveys/acs

183. SASUMMARY State annual summary statistics: personal income, GDP, consumer spending, price indexes, and employment. U.S. Bureau of Economic Analysis. Accessed March 15, 2023. https://apps.bea.gov/

184. Status of State Action on the Medicaid Expansion Decision. Kaiser Family Foundation. Published February 16, 2023. Accessed March 20, 2023.

https://www.kff.org/health-reform/state-indicator/state-activity-around-expanding-medicaid-under-the-affordable-care-act/

185. State Paid Family Leave Laws Across the U.S. Bipartisan Policy Center. Published January 13, 2022. Accessed March 20, 2023. https://bipartisanpolicy.org/explainer/state-paid-family-leave-laws-across-the-u-s/

186. Why the U.S. needs a $15 minimum wage: How the Raise the Wage Act would benefit U.S. workers and their families. Economic Policy Institute. Accessed April 12, 2023. https://www.epi.org/publication/why-america-needs-a-15-minimum-wage/

187. Ross M, Bateman N. *Meet the Low-Wage Workforce*. Metropolitan Policy Program at Brookings; 2019. https://www.brookings.edu/wp-content/uploads/2019/11/201911_Brookings-Metro_low-wage-workforce_Ross-Bateman.pdf

188. Cengiz D, Dube A, Lindner A, Zipperer B. The Effect of Minimum Wages on Low-Wage Jobs. *The Quarterly Journal of Economics*. 2019;134(3):1405-1454. doi:10.1093/qje/qjz014

189. Hickman M, Hughes K, Storm K. *Medical Examiners and Coroners' Offices, 2004.*; 2007.

190. Maguire-Jack K, Johnson-Motoyama M, Parmenter S. A scoping review of economic supports for working parents: The relationship of TANF, child care subsidy, SNAP, and EITC to child maltreatment. *Aggression and Violent Behavior*. 2022;65:101639. doi:10.1016/j.avb.2021.101639

191. Klevens J, Barnett SBL, Florence C, Moore D. Exploring policies for the reduction of child physical abuse and neglect. *Child Abuse & Neglect*. 2015;40:1-11. doi:10.1016/j.chiabu.2014.07.013

192. Klevens J, Luo F, Xu L, Peterson C, Latzman NE. Paid family leave's effect on hospital admissions for pediatric abusive head trauma. *Injury Prevention*. 2016;22(6):442-445. doi:10.1136/injuryprev-2015-041702

193. Brown ECB, Garrison MM, Bao H, Qu P, Jenny C, Rowhani-Rahbar A. Assessment of Rates of Child Maltreatment in States With Medicaid Expansion vs States Without Medicaid Expansion. *JAMA Netw Open*. 2019;2(6):e195529.

194. Schnitzer PG, Slusher PL, Kruse RL, Tarleton MM. Identification of ICD codes suggestive of child maltreatment. *Child Abuse Negl*. 2011;35(1):3-17. doi:10.1016/j.chiabu.2010.06.008

195. Dougall N, Savinc J, Maxwell M, et al. Childhood adversity, mental health and suicide (CHASE): a methods protocol for a longitudinal case-control linked data study. *Int J Popul Data Sci*. 5(1):1338. doi:10.23889/ijpds.v5i1.1338

196. Savinc J. "Schnitzer" codes (indicative of maltreatment) [ICD-10 crosswalk]. Published online December 2, 2021. Accessed March 8, 2023. https://github.com/jsavinc/CHASe-outside-safe-haven

197. Cunningham S. Causal Inference II. Presented at: Mixtape Sessions; March 16, 2024; Virtual. https://www.mixtapesessions.io/session/ci_ii_mar16/

198. Callaway B, Goodman-Bacon A, Sant'Anna PHC. Difference-in-Differences with a Continuous Treatment. Published online July 9, 2021. Accessed June 29, 2023. http://arxiv.org/abs/2107.02637

Appendices

Appendix A: Survey instrument used to assess the food security of households in the Current Population Survey food security supplement

Adapted from the USDA, Economic Research Service report 325: Household Food Security in the United States in 2022.[33]

Food security supplement questions for all households

1. "We worried whether our food would run out before we got money to buy more." Was that often, sometimes, or never true for you in the last 12 months?
2. "The food that we bought just didn't last, and we didn't have money to get more." Was that often, sometimes, or never true for you in the last 12 months?
3. "We couldn't afford to eat balanced meals." Was that often, sometimes, or never true for you in the last 12 months?
4. In the last 12 months, did you or other adults in the household ever cut the size of your meals or skip meals because there wasn't enough money for food? (Yes/No)
5. (If yes to question 4) How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?
6. In the last 12 months, did you ever eat less than you felt you should because there wasn't enough money for food? (Yes/No)
7. In the last 12 months, were you ever hungry, but didn't eat, because there wasn't enough money for food? (Yes/No)
8. In the last 12 months, did you lose weight because there wasn't enough money for food? (Yes/No)
9. In the last 12 months, did you or other adults in your household ever not eat for a whole day because there wasn't enough money for food? (Yes/No)
10. (If yes to question 9) How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?

Food security supplement questions for households with children aged 0–17

11. "We relied on only a few kinds of low-cost food to feed our children because we were running out of money to buy food." Was that often, sometimes, or never true for you in the last 12 months?
12. "We couldn't feed our children a balanced meal, because we couldn't afford that." Was that often, sometimes, or never true for you in the last 12 months?

13. “The children were not eating enough because there wasn’t enough money for food.” Was that often, sometimes, or never true for you in the last 12 months?
14. In the last 12 months, did you ever cut the size of any of the children’s meals because there wasn’t enough money for food? (Yes/No)
15. In the last 12 months, were the children ever hungry because there wasn’t enough money for food? (Yes/No)
16. In the last 12 months, did any of the children ever skip a meal because there wasn’t enough money for food? (Yes/No)
17. (If yes to question 16) How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?
18. In the last 12 months, did any of the children ever not eat for a whole day because there wasn’t enough money for food? (Yes/No)

Coding of responses to assess food security status

Questions 1–3 and 11–13 are coded as affirmative (i.e., possibly indicating food insecurity) if the response is “often” or “sometimes.” Questions 5, 10, and 17 are coded as affirmative if the response is “almost every month” or “some months but not every month.” The remaining questions are coded as affirmative if the response is “yes.”

Households without children are classified as food insecure if they report 3 or more indications of food insecurity in response to the first 10 questions; they are classified as having very low food security if they report 6 or more food-insecure conditions out of the first 10 questions.

Households with children (aged 0-17) are classified as food insecure if they report 3 or more indications of food insecurity in response to the entire set of 18 questions; they are classified as having very low food security if they report 8 or more food-insecure conditions in response to the entire set of 18 questions.

Appendix B: Discussion on two-way fixed effects model biases and methods for overcoming them

Technical details summarized in part from Scott Cunningham's Causal Inference II Mixtape Session, presented virtually on March 16, 2024.[197]

Two-way fixed effects (TWFE) models are commonly used in difference-in-difference analyses to examine the impact of policy interventions. The canonical difference-in-difference estimator estimates the average treatment effect on the treated (ATT) by comparing the pre- and post-treatment outcomes between a group that receives the treatment (the "treated") and a group which does not (the "control") over two time periods (pre-treatment vs post-treatment). This can be calculated by: subtracting the average of post-treatment outcomes from the average of pre-treatment outcomes for the treated group, subtracting the average of post-treatment outcomes from the average of pre-treatment outcomes for the control group, and then taking the difference of the two. Alternatively, a linear TWFE model (Equation B1) can be used. The TWFE model includes a binary fixed effect term for the treatment, a binary fixed effect term for time (pre- vs post-treatment), and an interaction of the two. The equivalent ATT is then given by the coefficient on the interaction term.

$$Y_{ist} = \beta_0 + \beta_1 * Treatment_{is} + \beta_2 * Post_t + \beta_3 * (Treatment_{is} * Post_t) + \varepsilon_{ist} \qquad \text{(Eq. B1)}$$

Where: y_{ist} is the outcome variable for unit i in group s at time t: β_0 is the intercept, representing the baseline prevalence of the outcome in the (untreated) control group in the pre-period; $Treatment_{is}$ is a binary variable indicating whether or not unit i in group s received the treatment (1 if treated; 0 if not) with β_1 representing the average treatment effect on the control group; $Post_t$ is a binary variable representing the time period after the treatment was introduced (1 if post-treatment; 0 if pre-treatment) with β_2 representing the average time trend in the control group; β_3 is the coefficient of interest, representing the average treatment effect on the treated (ATT) or the differential change in the outcome between the treatment and control groups after the treatment; ε_{ist} is residual unit-level variation.

The TWFE estimator has also been extended to include more than two groups who receive treatment at different points in time (Equation B2). This is known as "differential timing." In this case, the coefficient (β_3) on the treatment dummy variable (D_{ist}) represents a weighted average over all underlying treatment effects and thus estimates the ATT.

$$Y_{ist} = \beta_0 + \beta_1{*}G_s + \beta_2{*}T_t + \beta_3{*}D_{ist} + \varepsilon_{ist} \qquad \text{(Eq. B2)}$$

Where: y_{ist} is the outcome variable for unit i in group s at time t: β_0 is the intercept; G_s is a fixed effect for group s with β_1 representing the average treatment effect for that group; T_t is a fixed effect for time period t with β_2 representing the average time trend for time period t; and D_{ist} is a binary treatment indicator indicating whether or not unit i in group s was treated at time t with β_3 representing the coefficient of interest (ATT); ε_{ist} is residual unit-level variation.

Recent research however has uncovered biases in the TWFE model under differential timing scenarios.[26–30] In particular, the weighted average estimated by β_3 uses already treated units as a comparison, introducing heterogeneity bias in the estimate. For this reason, either constant treatment effects must be assumed or alternative estimators must be used to obtain an unbiased ATT estimate.[26,28–30]

While main analyses presented in this paper do not use a binary indicator to denote policy treatment, similar concerns have been raised for difference-in-difference analyses using TWFE estimators with continuous treatment variables.[198] Work in this area is currently ongoing, but it is important to note that the continuous TWFE difference-in-difference model specification includes an interaction of a variable that measures the continuous treatment (D_{ist}) with an indicator variable for the post-treatment period ($Post_t$) (Equation B3). Models in this dissertation do not take this form and therefore the concerns regarding TWFE estimators may not apply to results from these studies.

$$Y_{it} = \beta_0 + \beta_1{*}U_i + \beta_2{*}T_t + \beta_3{*}D_{ist}{*}Post_t + \varepsilon_{it} \qquad \text{(Eq. B3)}$$

Where: y_{it} is the outcome variable for unit i at time t: β_0 is the intercept; U_i is a fixed effect for unit i with β_1 representing the average treatment effect for that unit; T_t is a fixed effect for time period t with β_2 representing the average time trend for time period t; D_{ist} is a continuous variable measuring the treatment dose of unit i at time t and $Post_t$ is an indicator variable denoting the post-treatment time period with β_3 representing the coefficient of interest for the average treatment effect; ε_{it} is residual unit-level variation.

Out of an abundance of caution, however, we present, in addition to the main TWFE models in Chapters 2, 3, and 4, alternative non-TWFE models which would not be subject to these concerns. Instead of fixed effects for groups (or units) and time, hybrid fixed-effects models utilize group-specific means of the exposure variable to control for confounding between the exposure and time-specific means of the exposure variable to control for confounding between the exposure and time.[103]

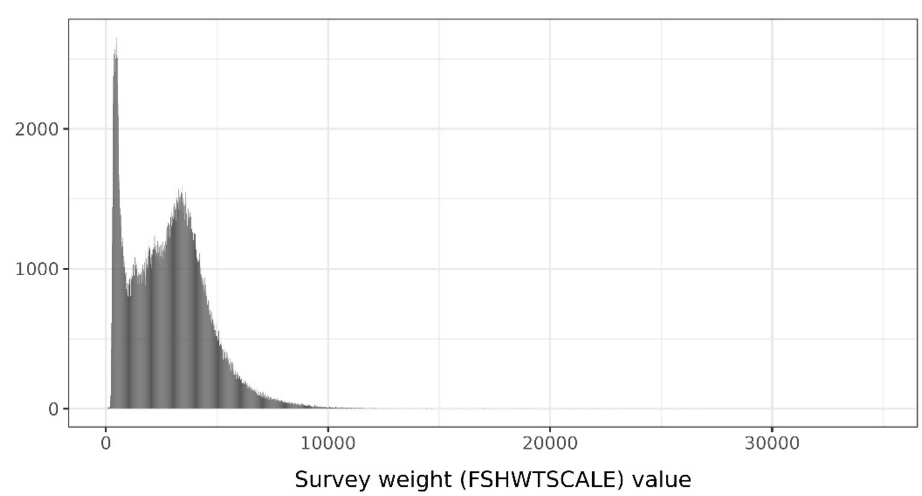
Appendix C: Discussion on the use of survey weights and resulting precision

While there is broad consensus that survey weights are necessary for obtaining population-representative descriptive statistics, their utility for providing unbiased regression-based estimates is contested.[99,124] Though not guaranteed to do so, the inclusion of survey weights often increases variability thereby reducing precision. Thus, most practitioners prefer to omit survey weights if doing so will not result in biased estimates. That said, one primary reason for including survey weights in causal analyses is to correct for heteroskedasticity and obtain more precise estimates.[99] For example, if the regression includes fixed effects for state and year, but the sample size for each state-year varies greatly, it may be necessary to correct for population-size-related heteroskedasticity in the state-year error terms. More generally, weighting can improve the precision of estimates (sometimes by a lot) if the following conditions hold: (1) the variance of the group-average error term is small, and (2) the within-group sample size is highly variable and small in some groups.[99]

In both Chapters 2 and 3, the inclusion of survey weights did not materially affect point estimates compared to unweighted analyses, suggesting little difference in bias between analytic models. However, in both chapters, weighted analyses were much more precise compared to unweighted analyses.

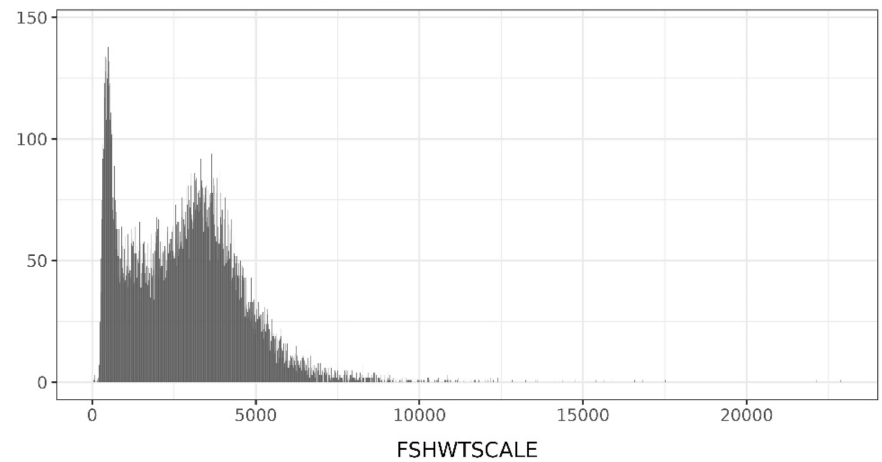
Examining the distribution of survey weights in Chapter 2 (Figure C1) we see highly variable weights, ranging from 48 to 34,817.

Figure C1: Distribution of survey weights among working aged households in the Current Population Survey in Chapter 2



Similarly, examining the distribution of survey weights in Chapter 3 (Figure C2) we again see highly variable weights, ranging from 54 to 22,878.

Figure C2: Distribution of survey weights among SNAP households in the Current Population Survey in Chapter 3



Survey weights are inversely proportional to the sample size of the population they represent. The distribution of survey weights for the Current Population Survey samples used in both Chapters 2 and 3 confirm that within-group sample size is highly variable and indeed small in some groups. Given this, and little observed evidence of additional bias compared to the unweighted models, the survey-weighted models are our preferred model specification.