Structural Responses to Structural Inequities: Evaluating the Potential of Earned Income Tax Credit (EITC) Policies as Tools for Addressing Social Inequities in Mental Distress

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Abstract

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Unjust systems of social hierarchy such as racism, sexism, and classism are pervasive in the United States today. They shape the opportunities, resources, and health of all members of society and contribute to substantial social inequities in health and economic wellbeing. As economic inequality and mental distress have concurrently worsened over recent decades and economic resources are an important determinant of mental health, there is reason to worry that these trends will have contributed to widening social inequities as well. However, the existing literature on this topic is inconsistent; varying depending on the time-period, measurement scale, level of social granularity, and social groups considered. This dissertation addresses these limitations by using repeated cross-sectional data from the Behavioral Risk Factor Surveillance System (BRFSS) to quantify trends in the prevalence of frequent mental distress (FMD) and social inequities in FMD between 1993 and 2019 for populations defined individually and intersectionally by sex, race, ethnicity, educational attainment, and household poverty status. In doing so, we find that the prevalence of FMD has increased substantially over recent decades across the social

spectrum; that social inequities in FMD have mostly widened over time in absolute terms while narrowing relatively; that those in poverty and low-socioeconomic status (SES) non-Hispanic white women in particular have seen the greatest increases in FMD and widening of social inequities in FMD over time; and that there are important within-group differences in FMD that would not have been identified if focusing on broad social groups alone.

As systems of social hierarchy and the social inequities they create are caused and upheld by structural factors (e.g., the ways our political and economic systems are organized, the policies we have adopted, and the built and social environment those policies have created), it is equally important that we identify how social policy has shaped social inequities in health over time and where social policy can be reformed to foster social equity instead of inequity. In this context, means-tested cash transfer policies such as the Earned Income Tax Credit (EITC) may be effective in mitigating rising mental distress and widening social inequities in mental distress. EITC policies in particular are some of the largest cash transfer programs in the US and have been shown to improve the economic wellbeing of recipients and reduce mental distress and disproportionately benefit socially disadvantaged groups. Practically, they have also been enacted (and so could be reformed) at state and federal levels and have already been expanded several times since their introduction in the 1970s.

For these reasons, this dissertation conducts two studies examining the relationship between EITC policies, economic wellbeing, FMD prevalence, and social inequities in each outcome. First, we use 2000-2019 BRFSS data to examine how refundable State EITC policies have been associated with longitudinal trends in FMD prevalence and social inequities in FMD between 2000 and 2019 for populations defined individually by sex, race and ethnicity, and household poverty status. In doing so, we find that states which historically offered a refundable State EITC policy saw smaller increases in FMD prevalence over time, comparatively narrowing sex- and poverty-based inequities in FMD, and contemporaneously lower FMD prevalence overall. However, our findings also suggest that State EITC policies have been associated with widening racial inequities in FMD over time for those non-Hispanic Black or Native American or Alaska Native (NAAN). In our second study, we use respondent information from the 2019 BRFSS and policy information from the University of Kentucky Center for Poverty Research (UKCPR) National Welfare Database to simulate how several Federal and State EITC reforms may have impacted national EITC expenditures, EITC recipiency rates, typical EITC credit eligibilities, and FMD prevalence in 2019 had they been implemented for the overall population as well as for groups defined individually by sex, race, ethnicity, educational attainment, and household poverty status. We find that these reforms could lift hundreds of thousands out of poverty and increase EITC benefits for millions more, while in most cases disproportionately benefiting socially disadvantaged groups. However, some of these reforms could also widen socioeconomic inequities and none of the reforms we considered would be expected to meaningfully affect FMD prevalence.

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Chapter 1.

Introduction

1.1.1 Background and Conceptual Motivation

Health inequities are avoidable, unjust differences in health between social groups or along social gradients stemming from oppressive systems of social hierarchy (e.g., racism, sexism, classism) that privilege some individuals at the expense of others.[1] Unfortunately, health inequities are the norm across most areas of health in the US instead of the exception. For example, of the 64 health and health care measures examined in the Kaiser Family Foundation (KFF) 2023 Survey on Racism, Discrimination, and Health, Black respondents reported worse outcomes than white respondents in 48 cases (75%) and Native American or Alaska Native (NAAN) respondents reported worse outcomes in 45 cases (70%).[2] Likewise in a recent Global Burden of Disease study, authors found that Black and/or NAAN individuals reported the highest mortality of all racial groups for 18 of 19 broad causes (e.g., cardiovascular diseases, neoplasms, etc.).[3] In fact, health inequities tend to occur wherever disease can be avoided or treated. Phelan *et al.* demonstrated this in the context of adult mortality in the US, finding much larger differences in mortality between socioeconomic groups across 96 causes of death covering 84% of all deaths where causes of death were preventable as opposed to not preventable.[4] Delavar *et al*. found similar results comparing differences in child and adolescent cancer survival across racial groups in the US, with non-Hispanic Black and Hispanic children reporting worse cancer survival; particularly for cancers amenable to treatment.[5] These inequities can also be substantial, as is the case for infant mortality rates, where the infant mortality rate for Black women was more than twice that of white women in 2022.[6] Worryingly, evidence also suggests that while some health inequities have improved over time, others have either not improved or worsened over recent decades. For example, Anderson and Zimmerman report that social inequities in mortality broadly improved between 1969 and 2000 but have stagnated from 2000 to 2019 and worsened since 2000 among older adults.[7] Likewise, while Zimmerman *et al.* find racial disparities in general health improved between 1990 and 2017, income-based disparities worsened considerably.[8] While any inequity would be cause for concern, the fact these inequities occur across most areas of health, can be substantial, are demonstrably avoidable, and may in fact be worsening suggests that we as epidemiologists have a responsibility to identify the systemic drivers of these inequities and propose solutions to address them. To do otherwise would move us away from the root purposes of epidemiology in understanding the social patterning of disease and reify as 'natural' the unfair systems of social hierarchy that produce these inequities.

Although there are several contributing factors to these inequities, it is widely accepted that they are underpinned by differences in how effectively groups can access and make use of health-protecting resources such as money, knowledge, or social connections. In public health, one of the most influential theories for understanding health inequities is Link and Phelan's "fundamental cause theory",[9] which posits that certain causes of disease are "fundamental" to health (e.g., racism,[10] stigma,[11] and multi-factorial discrimination[12]) because they *embody* access to health-protecting resources. According to this theory, we would expect to see health inequities anywhere: 1) there is a hierarchical system of social standing (hereafter 'social hierarchies') that differently exposes individuals to a "fundamental cause", 2) this "fundamental cause" results in differential access to flexible resources, and 3) those resources can be used to prevent or treat poor health. This theory has been substantially developed since its introduction,[13,14] particularly in terms of identifying effective areas for intervention.[15,16] Another important theory for understanding and addressing health inequities is Diderichsen's model,[17] which focuses on the points at which systems of oppression affect health inequities as opposed to the 'resources' which mediate these effects. Under their model, systems of oppression determine where individuals 'stand' in social hierarchies and their position in these hierarchies in-turn shapes their exposure to common risk factors for disease; how vulnerable they are to disease when exposed; and what the consequences of disease will be for them when affected. Diderichsen *et al.* emphasize that each of these 'points' are potential areas where policy intervention could improve or worsen social inequities in health. While both have contributed to my own conceptual model of health inequities (Figure 1.1) and to this dissertation, I believe neither sufficiently focuses on the political economy of health inequity or on how it upholds systems of oppression over time.

The *political economy* as a field studies how economic and political structures interact to shape each other, the production and distribution of resources across society, and how those resources can be used. It has also been central in understanding how inequality persists and can be incentivized by our economic and political systems.[18–20] For example, Mills argued in 1956 that entrenched power groups (i.e., those with the capacity to shape social hierarchies and their position within them, e.g., men, whites, and those with wealth) coordinate across government and economic sectors in ways that skew the distribution of resources towards themselves.[21] Understood from this perspective, classism, racism, and sexism are all incentivized under capitalism as means of reducing the cost of production and allowing greater resources to be distributed towards privileged groups (e.g., through women undertaking most unpaid domestic work[22] or through incarcerated men, the plurality of which are Black,[23] being forced to work for little to no pay[24]).[25] Our political system in turn enables this exploitation via laws and regulations, such as through our social assistance system under-funding childcare subsidies,[26] our tax system punishing dual-income households,[27,28] our law enforcement system disproportionately policing Black and brown communities,[29] and our labor rights and protections stopping short of shielding prisoners from exploitation and abuse.[24] Together, these economic and political structures uphold cultural expectations and prejudices underpinning social hierarchies (e.g., that a woman's primary role in society should be as a caregiver, or that Black people, particularly men, are inherently violent) and contribute to the differential resource access across groups that underpins health inequities. I believe that by studying the political economy of health inequity we can better understand historical trends in health equity over time and the social distribution of disease today; predict how health inequities may change in the future based on prevailing economic and political narratives; identify the most important structural factors that have perpetuated health inequities over time and contributed to their growth; and identify where systems change should be prioritized to incentivize health equity instead of inequity. For example, in a recent review of systematic reviews assessing the impact of the political economy on population health generally, McCartney *et al.* concluded that the rapid adoption of capitalism in Eastern Europe, political disenfranchisement of minoritized groups in the US, greater income inequality in the US (and elsewhere, to a lesser extent), the adoption of neoliberal economic policy and, counter-intuitively, Nordic-style welfare were all associated with greater health inequities (though welfare states were also associated with better health overall).[30] The same review also concluded that decreasing economic and social inequities, curbing 'unhealthy consumption' through regulation and taxation, and removing structural and financial barriers to accessing services were the most effective means of reducing health inequities.

Each of the above theories as well as intersectionality, discussed in Chapter 2, have contributed to my own conceptual model of health inequities (Figure 1.1) and the goals of this dissertation. To explain this model briefly, I theorize that the political economy at any time is shaped by historical policies, cultural norms, and group power relations. For example, much of our tax, social assistance, and labor policy today has been shaped by neoliberal economic doctrine coined in the immediate pre-War period and embraced by mainstream economic institutions and government under Presidents Carter and Reagan.[31] These systems in turn can bolster or challenge existing social hierarchies through structural policy which can have direct impacts (e.g., like the Civil Rights Act of 1964 which prohibited discrimination on the basis of several protected classes including race or sex) or indirect impacts through reshaping the distribution of resources across society (e.g., as the Tax Cuts and Jobs Act of 2017 did, disproportionately lowered the federal tax rate for the top percent of households by income[32]). This model also presumes that individuals and groups occupy unique social positions in society based on their co-occurring social identities under co-constituting systems of social hierarchy,[33] and that this position shapes individual access to flexible resources as well as how effectively those resources can be used to prevent or treat poor health. This can be immediate or occur over longer timeframes, such as through collective political action to change the political economy. Likewise, I theorize that the social distribution of disease and 'unhealthy behaviors' are used to justify or minimize the systems of oppression causing them (e.g., as we see now with the vilification and criminalization of homelessness[34]).

1.1.2 Rationale for Specific Dissertation Aims, Exposures, and Outcomes

With this background, my dissertation describes historical trends in mental distress and social inequities in mental distress across the US over recent decades, examines whether these trends have been positively shaped by the availability of State EITC policies, and identifies ways in which EITC policies could be reformed to make them more effective tools for improving health and social inequity. In doing so, I hope to encourage other epidemiologists to grapple with the political economy of health and social equity in their work; to investigate how economic and political structures shape the distribution of resources and opportunities across society in ways that cause the social patterning of disease; and to identify and advocate for structural change which can transform our political economy from one perpetuating oppression into one empowering all members.

I specifically focus on economic resources because existing literature suggests that some of the largest political economy drivers of health inequities are economic in nature: economic inequality, neoliberal economic restructuring, and financial barriers to accessing services.[8,30,35] I likewise focus on EITC policies because they are some of the largest means-tested cash transfer policies in the US,[36] because they disproportionately benefit socially disadvantaged groups,[37] and because they have exhibited variable availability, generosity, and eligibility criteria across the US over time, facilitating our analyses. Likewise, while conditional cash transfer policies like the EITC show some of the weakest relationships to mental health of all cash transfer policies,[38] they have unfortunately been the political reality of social assistance policies in the US over recent decades and so are the most relevant for explaining mental health inequity trends broadly. Relatedly, with an eye towards producing actionable evidence, these policies have garnered substantial political attention over recent years at state and federal levels[39] and so are directly relevant to current policymaking.

While my conceptual model of health inequities is purposefully not specific to one outcome, I chose to focus on mental health disorders in this dissertation for several reasons. First, mental health disorders are one of the leading causes of disease burden in the United States. According to the Global Burden of Disease (GBD) study, mental health disorders accounted for 17% of all years lived with disability in 2021 and 7% of all disability-adjusted life years, reflecting the years of 'full health' lost to disease.[40] These disorders also affect a significant portion of the population, with nearly one in four adults affected in the past-year in 2023[41] and nearly half of all people affected at some point in life[42] according to some estimates. As such, mental health disorders are a significant public health concern warranting attention. Moreover, as literature suggests that the prevalence and cumulative burden of mental health disorders has increased over time, particularly for anxiety[43] and depression[43–45] and among adolescents and young adults,[46–48] there is an urgent need to understand why and how we can reverse these trends. Likewise, as socially disadvantaged groups are disproportionately exposed to common risk factors for mental distress throughout life[49] and typically report greater mental distress,[44,50,51] it is important to understand whether this increase in burden has been universal or specific to socially disadvantaged groups. However, existing literature on this topic has reached mixed conclusions depending on the outcome, social axes, time-period, and measurement scale considered. Finally, there is extensive literature supporting income and wealth as strong determinants of mental health and health equity,[52–57] suggesting that this outcome would be sensitive to recent changes in EITC policies.

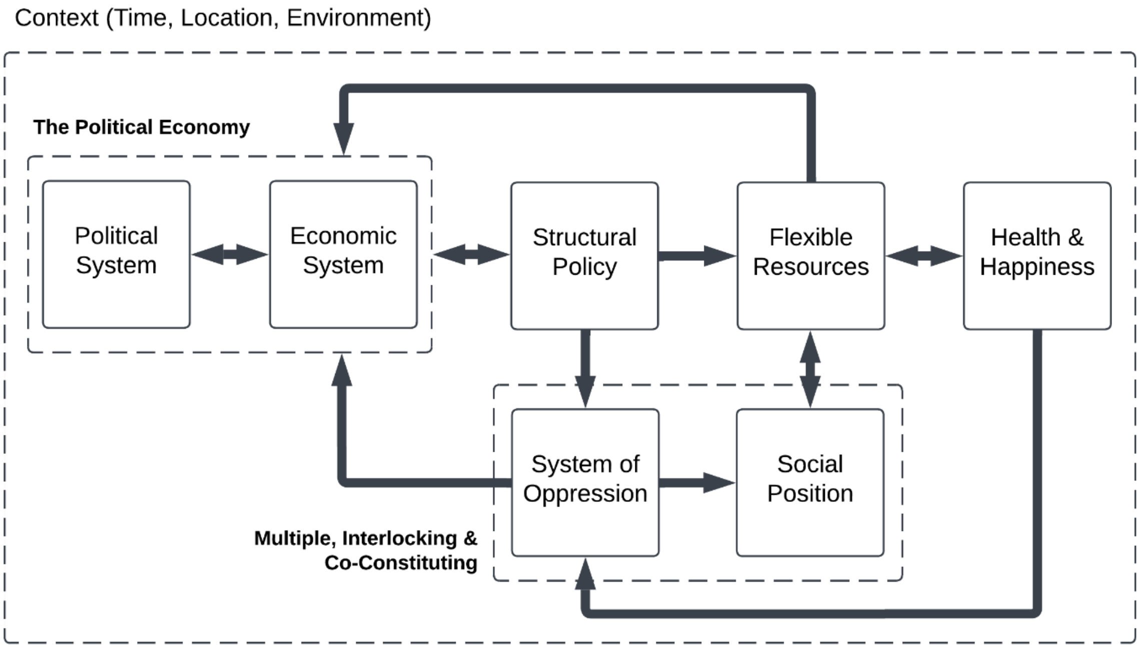
In Chapter 2, I describe historical trends in mental distress and social inequities in mental distress at the national level between 1993 and 2019 for social groups defined individually and jointly by sex, race, ethnicity, educational attainment, and household poverty status. This greatly improves upon the timespan and social granularity of most existing studies of health and health equity trends,[58] serves as the basis for Chapter 3, and allows us to contextualize recent mental health inequity trends in terms of several recent changes to the political economy. Next in Chapter 3, I assess whether the historical availability of refundable State EITC policies has been associated with trends in mental distress and social inequities in mental distress at the national level between 2000 and 2019 for social groups defined individually by race and ethnicity, sex, and household poverty status. Based on my conceptual model, we would anticipate that structural policies improving access to flexible resources would be associated with lower contemporaneous social inequities in mental distress and comparatively 'better' historical trends in the magnitude of health inequities over time. Further, as EITC policies are not typically evaluated in terms of their long-term population health and health equity impacts, I expect this analysis could provide a new motivation for expanding EITC policies. Finally in Chapter 4, I simulate the potential impact that several equity-oriented state and federal EITC policy reforms could have had on social inequities in poverty, economic wellbeing, and mental distress in 2019 had they been implemented, overall and for social groups defined individually by sex, race, ethnicity, educational attainment, and household poverty status. While this study does not capture the potential long-term impact of any reform, I would expect that these reforms would disproportionately increase resource access for socially disadvantaged groups and in turn lessen social economic and mental health inequities. I conclude in Chapter 5 by discussing the implications of Chapters 2-4 for future research, policy prioritization, and policy development.

1.1.3 Positionality and Reflexivity

Especially in the context of this dissertation which focuses on social equity, it is important to note that how I think about health and social equity, prioritize research questions, decide on how best to ask and answer those questions, and advocate for social change are all inseparable from my lived experiences, identities, and privilege. While I have strived to conduct this project with humility, to learn from those with different lived experiences than myself, and to practice reflexivity when interpreting my findings, I encourage readers to consider my positionality as well as their own in interpreting my findings and to recognize that the conclusions I reach will have been shaped by cultural blind-spots, internalized preconceptions, and my own socially conditioned idea of what is right and wrong. To make readers aware of my own positionality so that they can interpret my findings in context, I am a white, autistic, cis-gender man, I have a history of poor mental health, and I was raised in a low-income, predominantly single-parent household in Scotland. These experiences have undoubtedly shaped my interest in understanding mental health disorders and my focus on economic inequality as a driver of health inequities. However, I recognize that this may under-count the importance of non-economic modes of inequality; many of which I as a white, cis-gender man have actively benefited from. Likewise, while the United Kingdom's history is steeped in colonial conquest and imperialism and the UK participated extensively in the trans-Atlantic slave trade, Scotland's population demographics and social history are markedly different to the US; particularly concerning race, racism, and anti-Blackness.

1.1.4 Relevant Tables and Figures

Figure 1.1. Conceptual model of health inequities.



Legend: Solid arrows indicate theorized directions of effect between model nodes. Dashed lines indicate that nodes together constitute a larger social construct or 'node' whose effects are more than just the sum of its parts, such as the political economy, multidimensional social identity, and social context.

Chapter 2.

Intersectional Trends in Poor Mental Health and Health Inequities Across the US.

Intersectional Trends in Poor Mental Health and Health Inequities Across the US.

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Abstract:

Though mental distress poses a large and growing threat to population health, our understanding of how its social distribution has changed over time and what these changes imply for mental health equity is limited. To address this, we use data from the Behavioral Risk Factor Surveillance System to non-parametrically describe how age-standardized prevalence of frequent mental distress (FMD) and social inequities in FMD have changed in the United States between 1993 and 2019 for intersectional social groups defined by ethnicity, race, sex, educational attainment, and household poverty status. We find that age-standardized FMD prevalence has increased for almost all social groups, that health inequities between more and less privileged groups have mostly widened in absolute terms but narrowed relatively, and that relying solely on common group FMD summaries masks substantial heterogeneity across intersectional subgroups. Our findings show an urgent need to address the sociopolitical determinants of mental distress, prioritizing policies which would address the growing inequitable burden experienced by those less privileged.

2.1. Introduction

2.1.1 Background

Descriptive epidemiology is essential for effective and equitable public health planning, causal research, and policy development.[59] By understanding the 'Who, What, When, and How Much?' of a disease, we can allocate finite health resources, target them to the most affected populations,[60] generate hypotheses about the causes and distribution of disease, and design policies and interventions to reduce disease burden and promote health equity. This research is especially needed to understand and address recent trends in population mental health and health inequities.

As a leading cause of disease burden in the United States,[61] mental health disorders significantly shape population health equity. They affect one in five people concurrently, most individuals during their lifetime,[62] and disproportionately burden social groups marginalized by systems of oppression like sexism or classism.[44,50,51] As common mental health disorders like depression and anxiety are increasingly prevalent,[51,63–65] there is an urgent need to understand when and among whom this burden has increased, as well as how these changes have affected mental health equity. As we show in Section 2.1.2, these questions are difficult to answer given the lack of available information on mental health trends for intersectional social groups.[58]

2.1.2 Existing Literature on Trends in Population Mental Health and Health Inequities

An extensive scholarly and grey literature has assessed trends in population mental health and health inequities over time among US adults,[40,43–45,50,63,66–70] which we review in-detail in Appendix 2.A focusing on the social axes assessed in our study. This literature mostly concludes that population mental health has declined over time while mental health inequities have changed variably depending on the outcome, social axes, period, and measurement scale considered. While this literature typically presents disaggregated trends for common social groups (i.e., those defined by a single social axis, e.g., sex), they rarely consider how trends vary for populations defined across multiple social axes intersectionally.[58] From our review, we only identified three studies examining intersectional trends in population mental health.[44,66,71] Peele[66] examined trends in mental illness and anxiety for non-Hispanic whites by education level, finding broadly similar trends across groups, and Todd and Teitler[44] examined trends in depression by sex and either education or income, again finding similar within-sex trends. Evans and Erickson[71] by contrast compared changes in depression over time for the same intersectional groups defined by gender, race and ethnicity, income, and immigrant status while adolescents in 1994/5 and young adults in 2008, finding depressive scores rose significantly for Black men and women, and white men, and fell significantly for Latinx women and low-income Latinx men. However, while informative, their findings cannot be generalized to all adults or identify when changes occurred.

We expand on this literature by conducting a descriptive analysis of trends in population mental health and health inequity among US adults between 1993 and 2019, using the annual average past-month prevalence of frequent mental distress (FMD) as our mental health measure. We examine trends for intersectional social groups defined jointly by interviewer-presumed sex, self-identified race and ethnicity, educational attainment, and household poverty status. Consistent with our intersectional framework, we explicitly frame differences in mental health between groups as 'inequities' rather than 'inequalities', presuming they are predominantly caused by unjust, prejudicial systems of social hierarchy operating at the micro-, meso-, and macro-level (i.e., systemically) to differentially shape individuals' ability to access and make use of scarce health-promoting resources and opportunities.[1,72,73]

To make our findings more useful to other researchers, health practitioners, and policymakers, we also provide an extensive supplementary dataset available at https://github.com/kblaikie/MH_inequity_trends containing year-specific group prevalence and inequity estimates with associated uncertainty bounds for 242 nested social groups and 31 nested social inequities defined individually and intersectionally over our study period.

2.1.3 Study Rationale

Developing a more nuanced understanding of population mental health and its social distribution would bolster our ability to improve social health equity. Our study is designed to elicit such an understanding while providing actionable evidence relevant to policy development. We do so following three equity-oriented recommendations: 1) to describe intersectional heterogeneity in health outcomes within and across common social groups,[74] 2) to report health inequities using the measuring scale(s) most consistent with our goals and equity framing,[75,76] and 3) to explicitly examine trends in health inequities over time.[14]

2.1.3.1 Describing Intersectional Heterogeneity in Outcomes Within and Across Social Groups

In *Rethinking Social Epidemiology,* Lofters and O'Campo suggest social epidemiologists can produce more actionable research by 1) centering in their work the macro-level systems of oppression which create health inequities, and 2) examining heterogeneity in health outcomes within and across commonly defined social groups. For these reasons we adopt an intersectional theoretical and analytic framework in our analysis.

Intersectionality contends that how individuals identify and the social privilege or oppression they experience is shaped jointly and non-additively by their social positions across multiple interlocking and co-constituting systems of power.[33,72] Black feminist legal scholar Kimberlé Crenshaw coined the term "intersectionality" while advocating for a new form of intersectional analysis in the 1980s. Crenshaw argued that by treating racism and sexism as independent, anti-discrimination doctrine and social discourse implicitly centered the experiences and needs of more privileged marginalized individuals (e.g., Black men in antiracist discourse and white women in Feminist discourse), perpetuating the subordination of less privileged individuals (e.g., Black women, whose discrimination in the labor market was due to them being Black *and* women).

Adopting an intersectional framework offers several conceptual and practical advantages relevant to understanding population mental health and improving social equity. It encourages researchers and policymakers to develop a more nuanced understanding of multi-dimensional privilege and the social production of disease; to prioritize interventions targeting systems of oppression in ways atheoretical analyses may not;[74] to design interventions with those holding multiple marginalized identities in-mind;[77,78] and to consider how systems of oppression interact when evaluating the effectiveness of interventions. More immediately, intersectionality can help identify who public health initiatives should target to best-improve health equity.[60]

Intersectionality was central to how we designed our study (see Section 2.2), the information available in our supplemental dataset (e.g., mental health summaries at different levels of social disaggregation to facilitate inter- and intra-categorical intersectional analyses),[79] and the research questions we address in this article (see Section 2.1.4).

2.1.3.2 Describing Social Inequities Using the Most Appropriate Measurement Scale

Social inequities are commonly defined in absolute terms (e.g., via a prevalence difference) or relative terms (e.g., via a prevalence ratio), and researchers may prefer to use one scale over another for substantive, normative, mathematical, or practical reasons.[75,76,80] While this choice and its rationale are not usually stated, many argue they should be for various reasons. According to Asada,[81] each scale is better-suited for answering different equity-related questions, with relative measures more applicable for understanding etiology and absolute measures more relevant for policy impact evaluations and tracking population health. As Harper *et al.* explains,[76] each scale also endorses a different normative framing of equity shaping how we prioritize interventions and evaluate their effectiveness. As relative measures do not consider the base occurrence of disease, they implicitly equate equity with equality, taking a strictly egalitarian stance. Absolute measures by contrast adopt a more pragmatic stance, acknowledging that minimizing differential disease burden is also important. Finally, as the relationship between overall disease burden and inequity magnitude is mathematically predictable on each scale[80] and researchers typically only present one,[82] choosing which scale to use often shapes how we interpret changes in social equity across contexts (e.g., time, policy environment) where overall population health differs. For this reason, it is recommended authors either justify their choice in advance or report inequities on both scales.[83] As we do not approach our study with a specific normative framing of equity and would like our data to be informative in answering various questions, we present social inequities on both scales.

2.1.3.3 Describing Trends in Population Health and Health Inequities Over Time

Examining trends in population mental health and health inequity is important for several reasons, such as determining whether resources need to be reallocated in response to changing disease burden or inequity magnitude (e.g., during the COVID-19 pandemic where depression rose and social inequities in depression widened);[65] generating hypotheses around disease and inequity causation (e.g., the 'prevalence inflation hypothesis', as discussed in Section 2.4);[84] forecasting future resource needs; and evaluating the impacts of interventions, policies, and societal changes.[59] Sociologist Alicia Riley recently provided another rationale for assessing inequity trends over time, arguing that systems of oppression are themselves ubiquitous causes[85] in a population whose effects on health and intervenable pathways can only be understood by comparing across contexts (e.g., time) where those systems differ.[14] We explicitly assess how social inequity magnitude has changed over time for these reasons.

2.1.4 Research Questions

We aim to answer the following research questions:

1. How has overall FMD prevalence changed between 1993 and 2019?
2. How have trends in FMD prevalence varied across common and intersectional social groups, and what impact has this variation had on social inequities in FMD?
3. How have trends in FMD prevalence varied intra-categorically within common social groups?

Recognizing the broad scope of our study, we prioritize describing general findings across social groups, identifying those at either end of the social distribution, and noting where our inferences about social inequity depend on the measurement scale used.

2.2. Methods

2.2.1 Data

Researchers conducting quantitative intersectional analyses frequently limit the number of social intersections considered for practical reasons, such as the difficulty involved in generating precise, unbiased burden estimates for small or under-represented populations.[58,86] To avoid this, we used participant information from the 1993-2019 Behavioural Risk Factor Surveillance System (BRFSS): a set of state-administered Centers for Disease Control and Prevention (CDC) funded, telephone-based health surveys interviewing approximately 400,000 non-institutionalized US residents each year across the 50 states, District of Columbia (DC), Puerto Rico, Guam, and US Virgin Islands. BRFSS is the largest health survey globally, collecting extensive demographic, geographic, and health data, with mental health assessed from 1993 onwards. BRFSS employs complex sampling and weighting methodologies to provide valid and reliable state- and nationally representative population estimates overall and for key subpopulations.[87,88]

Our study population consisted of all BRFSS respondents residing in one of the 50 states or DC and self-identifying as white or Black, providing annual samples ranging from 87,000–384,000 individuals, with larger samples in later years. Those self-identifying as Asian, Native American or Alaska Native (NAAN), or Native Hawaiian or Pacific Islander (NHPI) were excluded from our primary analysis due to insufficient sample sizes, though less granular intersectional summaries are provided for these groups in Appendix 2.B. Respondents with missing information on any study variables were excluded, alongside all respondents in Puerto Rico, Guam, and the US Virgin Islands for whom we lacked consistent and equivalent state-level information to determine household poverty. Finally, we excluded all respondents from 2002 when our outcome measure was not included in the core BRFSS questionnaire administered in all states.

2.2.2 Measures

2.2.2.1 Outcome Measures

We used the CDC health-related quality of life (HRQOL) 'healthy days' indicator for mental health,[89] in which individuals are asked "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?". This indicator has good internal validity across demographic subpopulations and test-retest reliability across populations of non-institutionalized adults.[90] We created an indicator for annual past-month prevalence of frequent mental distress (FMD), typically defined as ≥14 mentally unhealthy days in the past month,[90] reflecting the symptom period often used for clinical depressive and anxiety disorders. As age is a strong predictor of mental distress[91] and age distributions vary over time and across demographic subpopulations, we age-standardized this indicator to reflect the national age distribution in 2000 (see Section 2.2.3.1.1).

2.2.2.2 Exposure Measures

We considered five social axes in our analysis: interviewer-presumed sex, self-identified race, self-identified ethnicity, highest educational attainment, and household poverty status. For brevity we only present findings in this article for common (i.e., single identity) groups (e.g., women) and intersectional groups defined by all axes jointly (e.g., Hispanic Black women with higher educational attainment, living in household poverty), though equivalent estimates are provided in our supplementary dataset for populations defined by all 1-5-way combinations of these axes, including Asian, NAAN, and NHPI populations.

2.2.2.2.1 Race

BRFSS has asked respondents to self-identify (classify) their race with varying phrasing, response categories, and single/multiple response options over time. During our study period, categories included white, Black, Asian or Pacific Islander, Native American or Alaska Native, and 'Other'.

2.2.2.2.2 Ethnicity

BRFSS has asked respondents to report their Hispanic and/or Latinx ethnicity in a manner consistent with minimum Office of Management and Budget (OMB) recommendations, disaggregated response options for ethnicity/country of origin from 2013 onwards.[92] We categorize respondents as Hispanic and/or Latinx or not Hispanic and/or Latinx (hereafter 'Hispanic' or 'non-Hispanic' for brevity).

2.2.2.2.3 Presumed Sex

BRFSS instructs interviewers to presume the sex of respondents and only ask respondents to self-identify when undecided. While the sexual orientation and gender identity (SOGI) optional module includes questions allowing respondents to indicate their sex at birth and gender identity, this module was inconsistently administered across states and over time. We therefore rely on interviewer-presumed sex, categorizing respondents as ‘presumed Male’ or ‘presumed Female’ (hereafter ‘male’ or ‘female’ for brevity).

2.2.2.2.4 Educational Attainment

Respondents self-reported their highest grade of educational attainment, with categories reflecting no schooling, elementary only, some high school, high school completion or a General Educational Diploma (GED), some college, and college completion. We categorized respondent’s as having “less than high school completion” or “high school completion or higher” (including those with a GED, which reflects an equivalent level of education) as high school graduation is typically the most informative educational milestone in terms of health disparities.[93]

2.2.2.2.5 Household Poverty Status

Respondents self-reported their annual household income using bracketed categories (e.g., $15,000 to $19,999). We converted these into continuous dollar amounts using the within-category uniform imputation approach proposed by the State Health Access Data Assistance Center (SHADAC).[94] This approach involved imputing continuous income at-random (i.e., uniformly) within reported income brackets and has been shown to perform better than alternatives at accurately imputing income for those lower on the income distribution. Using this imputed continuous income alongside information on respondent age, state of residence, household size, and number of dependents, we calculated each individuals’ absolute (household) poverty status by comparing their income against state-specific poverty thresholds provisionally based on the Census Bureau Official Poverty Measure (OPM),[95] categorizing respondents as ‘In Poverty’ or ‘Not In Poverty’.

To account for state differences in cost-of-living, OPM thresholds were adjusted by state before determining poverty status using the Bishaw Index[96,97] – a form of Median Rent Index (MRI) created at the Census Bureau reflecting the relative difference between state and national median gross rents – using rent information from the decennial census and American Community Survey (ACS). As state-specific gross median rent information was unavailable for 1993-1999 and 2001, we linearly imputed state median gross rents for these periods using 1990, 2000, and 2002 data. To account for inflation not related to housing costs, we adjusted nominal gross median rents prior to computing the Bishaw Index using the Consumer Price Index excluding shelter costs (CPI-LS) from the Bureau of Labor Statistics.[98] Finally, to account for uncertainty in each individual's actual household income, we repeated this income imputation 500 times, determining household poverty in each case and using these imputed incomes serially across bootstrap repetitions in generating 95% confidence intervals (see Section 2.2.3.3).

2.2.3 Statistical Analysis

2.2.3.1 Primary Analyses

We estimated the national annual past-month prevalence of FMD and social inequities in the prevalence of FMD at different levels of social disaggregation. Consistent with our intersectional framing, we anticipated non-linear trends in population mental health and health inequities over time, across social groups, and across levels of social stratification. As such, we conducted all analyses non-parametrically to avoid introducing distributional assumptions. To summarize trends over time, we present weighted average annual changes (AAC) for each outcome over the maximum longitudinal period available for each group, using the arithmetic mean for FMD prevalences and absolute inequities and the harmonic mean for relative inequities.

2.2.3.1.1 Absolute Mental Health

For each population of interest, we calculated FMD prevalence applying respondent composite weights 1) accounting for BRFSS design effects and achieving population representativeness and 2) age-standardizing each yearly population to the US age distribution in 2000. These respondent composite weights were constructed as the product of pre-existing BRFSS design weights and age-standardizing weights first-reported by Klein and Schoenborn.[99]

2.2.3.1.2 Social Inequities in Mental Health

We assessed absolute and relative social inequities in FMD prevalence using Prevalence Difference (PD) and Prevalence Ratio (PR) estimators, respectively. In each case, we used as referent the annual FMD prevalence of those conceptualized as most-privileged under each set of social stratifications (e.g., using those male for sex-based inequities or male, white, non-Hispanic, more educated, and not in poverty for inequities defined across all social axes). We presumed *a priori* that these individuals would likely experience better mental health than those with one or more marginalized identity, such that our inequity estimates could be interpreted as shortfalls in achievable population mental health. We did so explicitly to centre systems of oppression and those holding multiple marginalized identities in our analyses, as recommended by Bowleg.[78] We avoided using the national average as referent as it weights the mental health of larger social groups more heavily, who are disproportionately socially advantaged, while making it difficult to interpret our findings in the context of social oppression.

2.2.3.2 Data Suppression Approaches

To avoid presenting population summaries which are statistically unreliable, we masked FMD prevalence estimates following data suppression guidelines produced by the National Center for Health Statistics (NCHS),[100] discussed further in Appendix 2.C. We opted not to follow BRFSS guidelines as these largely rely on the relative standard error of point estimates, which can be overly conservative or liberal where point estimates are small or large respectively.[100] As a sensitivity analysis, we compared the number of estimates suppressed using NCHS and BRFSS guidelines in Appendix 2.C.

2.2.3.3 Confidence Bounds

We estimated percentile-based 95% confidence intervals (CI) for each outcome using a stratified bootstrapping approach with 500 repetitions, resampling individuals with replacement proportional to their intersectional group size in each year. This approach ensured all intersectional groups were retained in each annual bootstrap sample, so long as at least one group individual was originally present.

All analyses were performed in R Version 4.0.3[101] using the RStudio IDE.[102]

2.3. Results

2.3.1 Study Population and Suppressed Estimates

BRFSS interviewed 8,717,473 non-institutionalized adults between 1993 and 2019, with 6,382,175 (73%) meeting inclusion criteria for our primary analyses and 294,346 (3.4%) meeting inclusion criteria for our supplemental analyses of those Asian, NAAN, or NHPI. Our primary analysis population consisted of annual samples ranging from 86,550 respondents in 1993 to 383,576 in 2011, with a median annual sample of 272,033. Demographically, 91% of this eligible population self-identified as white, 42% were male, 10% were living in household poverty, 7.7% had less than high school completion, and 4.3% self-identified as Hispanic, with intersectional strata pooled across study years ranging in size from 782 respondents (for Hispanic Black women with less than high school completion who were not living in household poverty) to 2,757,936 respondents (for non-Hispanic white women with at least high school completion who were not living in household poverty) (Appendix 2.D).

After applying NCHS data suppression guidelines, zero FMD prevalence estimates were suppressed for any common social group and most intersectional groups. However, owing to very small sample sizes seven of eight Hispanic Black groups had over 50% of their prevalence estimates suppressed, limiting the comparability of their trend estimates. Additional sample size, estimate suppression, and mental health summaries are presented for intersectional groups in Appendices 2.C and 2.D.

2.3.2 Overall Trend

Between 1993 and 2019 age-standardized FMD prevalence increased on-average by 0.25 percentage-points (hereafter 'pp') each year. While this annual increase appears small, it corresponds to a 70.5% rise in FMD prevalence between 1993 and 2019 (Fig. 1), rising from 8.8% in 1993 (95% CI: 8.5% to 9.2%) to 15.1% in 2019 (95% CI: 14.8% to 15.4%). Similar national trends were observed without age-standardizing prevalence estimates, rising 64.0% from 8.5% in 1993 (95% CI: 8.2% to 8.8%) to 13.9% in 2019 (95% CI: 13.7% to 14.2%). Stratifying by age, overall trends were more pronounced for younger populations, while age-specific trends varied somewhat across common social groups (Appendix 2.E).

2.3.3 Trends Across Common Social Groups

Age-standardized FMD prevalence increased between 1993 and 2019 for all common social groups, with the smallest increase for those Hispanic (AAC: +0.11pp) and largest increase for those in poverty (AAC: +0.36pp) (Table 2.1). How these changes have impacted social inequities, however, depends on the social axes considered and measurement scales used. Summarizing trends qualitatively, ethnicity-based inequities reversed direction on both scales with Hispanics reporting lower FMD prevalence in 2019, race-based inequities narrowed on both scales with Black individuals reporting higher point-estimated prevalence in 2019, and sex, education, and poverty-based inequities widened in absolute terms while narrowing relatively, with those less privileged along each axis reporting higher FMD prevalence throughout our study period.

2.3.4 Trends Across Intersectional Social Groups

2.3.4.1. FMD Prevalence

Age-standardized FMD prevalence rose over our study period for 90% of intersectional groups (N=26 of 29, 3 suppressed), with a median AAC of +0.23pp (AAC IQR: +0.18pp to +0.48pp, Fig. 2A). Prevalence trends were only weakly associated with initial FMD prevalence, common social group identity, or multi-dimensional privilege, though two patterns emerged: 1) all three groups reporting the steepest increases in prevalence were non-Hispanic white women with less education and/or experiencing household poverty, and 2) Hispanic and non-Hispanic white groups differed in the direction of their trends, with Hispanic white groups disproportionately reporting lower-than-median increases (N=6 of 8, 75%) and non-Hispanic white groups reporting higher-than-median increases (N=6 of 8, 75%).

By 2019, age-standardized FMD prevalence ranged from 5.2% (for those Hispanic, white, male, not in poverty, and less educated) to 46.7% (for those non-Hispanic, white, female, in poverty, and less educated), with a median prevalence of 17.0% [IQR: 14.2%, 22.8%, 4 suppressed] (Fig. 2B). Groups reporting higher FMD prevalence were disproportionately in poverty and less educated, while those conceptually most privileged along every social axis (i.e., non-Hispanic, white, male, not in poverty, and more educated) consistently reported some of the lowest FMD prevalences throughout our study period (Fig. 2B).

2.3.4.2. Social Inequities in FMD Prevalence

Compared to our conceptually most-privileged referent group, social inequities mostly widened over time in absolute terms (N=19 of 28, 68%) with a median AAC of +0.06pp [IQR: -0.05pp, +0.23pp], while narrowing over time in relative terms (N=24 of 28, 86%), with a median multiplicative AAC of 0.98 [IQR: 0.96, 0.99] (Fig. 3). Less than half of all intersectional groups (N=13 of 28, 46%) reported the same direction of trends in equity when measured in absolute versus relative terms, with nine predominantly Hispanic groups reporting improvements on both scales and four non-Hispanic white groups (all in poverty and/or less educated) reporting declines on both scales. For all other groups, inequities worsened over time in absolute terms and improved in relative terms.

2.3.5 Trends Within Common Social Groups

We observed substantial variation in FMD prevalence trends and annual prevalences across the intersectional subgroups of each common group (Fig. 4). For example, while women as a whole reported an AAC of +0.27pp, the AAC reported by female intersectional groups ranged from -0.37pp to +1.03pp with an IQR of +0.08pp to +0.34pp. Comparing common groups, FMD prevalence trends varied least across Black intersectional groups [AAC IQR: +0.18pp, +0.35pp] and most across intersectional groups in poverty [AAC IQR: +0.13pp, +0.57pp], while 2019 FMD prevalences varied least across Hispanic groups [IQR: 12.6%, 16.7%] and most across white groups [IQR: 12.6%, 28.6%].

Of note, much of the variation in outcomes observed across common groups can be attributed to a small number of their larger intersectional subgroups. For example, two-thirds of intersectional groups experiencing poverty (N=10 of 15, 1 suppressed) reported smaller increases in FMD prevalence over time than those in poverty overall, while three-quarters of non-Hispanic intersectional groups (N=12 of 16) reported higher FMD prevalence in 2019 than non-Hispanics overall.

2.5. Discussion

To our knowledge, our study is the largest analysis of trends in intersectional mental health and health inequities to date, providing annual FMD prevalence estimates over a 27-year period for groups defined individually and intersectionally by ethnicity, race, sex, educational attainment, and household poverty status. We found that FMD prevalence increased over time for nearly all social groups, with less educated and/or impoverished non-Hispanic white groups reporting the largest increases in FMD over time. We also found that while social inequities in FMD mostly narrowed over time in relative terms, they primarily widened in absolute terms. While this partly reflects the mathematical bounding of inequity measures,[80] it also suggests our reliance on relative measures of inequity may be missing important changes in mental health equity over time. Finally, we observed substantial heterogeneity in annual FMD prevalences and prevalence trends across the intersectional subgroups of most common social groups.

Qualitatively, our conclusions agree with much of the existing literature concerning the social distribution of mental distress, how this burden has changed over time, and how social inequities have changed over time; all of which we discuss in-depth in Appendix 2.A. Our study further adds to this literature by providing a common set of prevalence trends which researchers can compare their findings against. For example, prior to our study Peele[66] conducted the longest intra-categorical analysis of US trends in population mental distress, comparing non-Hispanic whites by education. Supplemental data from our study could extend their analysis longitudinally and to other racial and ethnic groups, as well as allow for more granular intra-categorical comparisons by sex and household poverty status.

While our analysis did not seek to explain why mental distress is socially distributed as it is, our findings are consistent with several theories which address this question. For example, apart from Hispanics less privileged common social groups consistently reported greater mental distress than more privileged groups throughout our study period. This could be explained via Fundamental Cause Theory[9,16] and Diderichsen's model of health disparities,[17] which posit that resources are essential in protecting health and that social groups occupy different positions in systems of power which determine their access to resource and their efficacy in preventing mental distress. Conversely, our observation that holding multiple privileged identities does not necessarily confer lower mental distress can be understood by thinking intersectionally, since privilege and subordination under inter-connected systems of power coalesce in complex and non-additive ways to shape health.[72,103,104]

Intersectional theory can help explain why many intersectional groups holding privileged identities (e.g., being male, white, or non-Hispanic) reported higher mental distress in our study and why nine of the ten groups reporting the highest mental distress in 2019 were non-Hispanic. As Crenshaw explains, by thinking about societal privilege along unidimensional lines we implicitly centre the experiences of those holding multiple privileged identities.[72] In our context, the lower FMD prevalence of non-Hispanics as a whole is skewed by the much lower FMD prevalence reported by higher-socioeconomic status (SES) men, masking the experiences of most non-Hispanic groups who consistently reported higher FMD. As Purdie-Vaughns and Eibach[105] explain in their description of "intersectional invisibility", those holding one or more subordinated identity (e.g., non-Hispanic women in poverty) are typically excluded from our prototypical image of common social groups (e.g., non-Hispanics) such that in practice, they are less catered-to culturally, legally, and politically by the systems of power they provisionally benefit from.

Our finding that mental distress has become more prevalent across the social spectrum could be explained by considering how the changing political economy of health[18,19] has redistributed health-protecting resources across society.[20] Over recent decades US tax policy has become increasingly regressive,[106] social assistance policies have been restructured to provide 'workfare' instead of 'welfare',[107] states have facilitated wide-scale political disenfranchisement for partisan, business-friendly, and racist reasons,[108,109] and a majority of US industries have undergone extensive market consolidation,[110] limiting worker bargaining power, worsening job quality, and widening economic inequality.[111–113] Collectively, these changes have redistributed resources (e.g., capital, bargaining power, and political agency) from less to more privileged social groups and from the populace majority to an increasingly small minority, with potentially significant implications for population mental health. Given mental distress also predisposes individuals to future economic hardship,[114] rising inequality likely plays some part in explaining the broad declines in population mental health we observe.

Rising inequality is particularly cited as an explanation for increasing 'diseases of despair' among lower-SES white men,[115,116] which we observed. However, it is worth noting women and racially minoritized groups have also experienced rising inequality and continue to experience greater economic hardship than white men.[117–119] Other explanations for the rise in mental distress among lower-SES white groups include their lower optimism for the future,[120] a growing disconnect between their objective and perceived financial precarity,[121] and white paranoia concerning a loss of social status relative to historically minoritized groups.[66,122]

More broadly, non-economic explanations for declining population mental health include rising loneliness and physical inactivity[123] and cultural changes in how we think and talk about mental health. Over time mental health disorders have become increasingly recognizable and destigmatized,[124] which could lead individuals to more accurately endorse feeling mentally unhealthy. However, Foulkes and Andrews[84] propose in their 'prevalence inflation hypothesis' that increased mental health awareness could also be contributing to the over-pathologization of common psychological experiences[84] which, while not negating our findings, would suggest a growing disconnect between self-reported and clinically diagnosed disorders. As destigmatization has been greatest amongst younger age groups and generational cohorts,[124] this could be especially relevant in explaining reported declines in adolescent mental health[48] and our finding that FMD has risen most among 18-24 years-olds.

These non-economic explanations could be particularly informative in explaining our findings for Black and Hispanic populations who have reported smaller rises in mental distress than similar white groups despite their materially greater financial hardship.[113,125,126] Conversely the 'Hispanic paradox', where Hispanic and/or Latinx immigrants tend to report better mental health than US-born individuals,[127] is an unlikely explanation for our observed trends given US-born Hispanics have constituted a growing share of Hispanics since 2000,[128] US-born Hispanics tend to report worse mental health than foreign-born Hispanics,[129] and trends in mental health for immigrant and non-immigrant Hispanics since the late-1990s appear similar.[71]

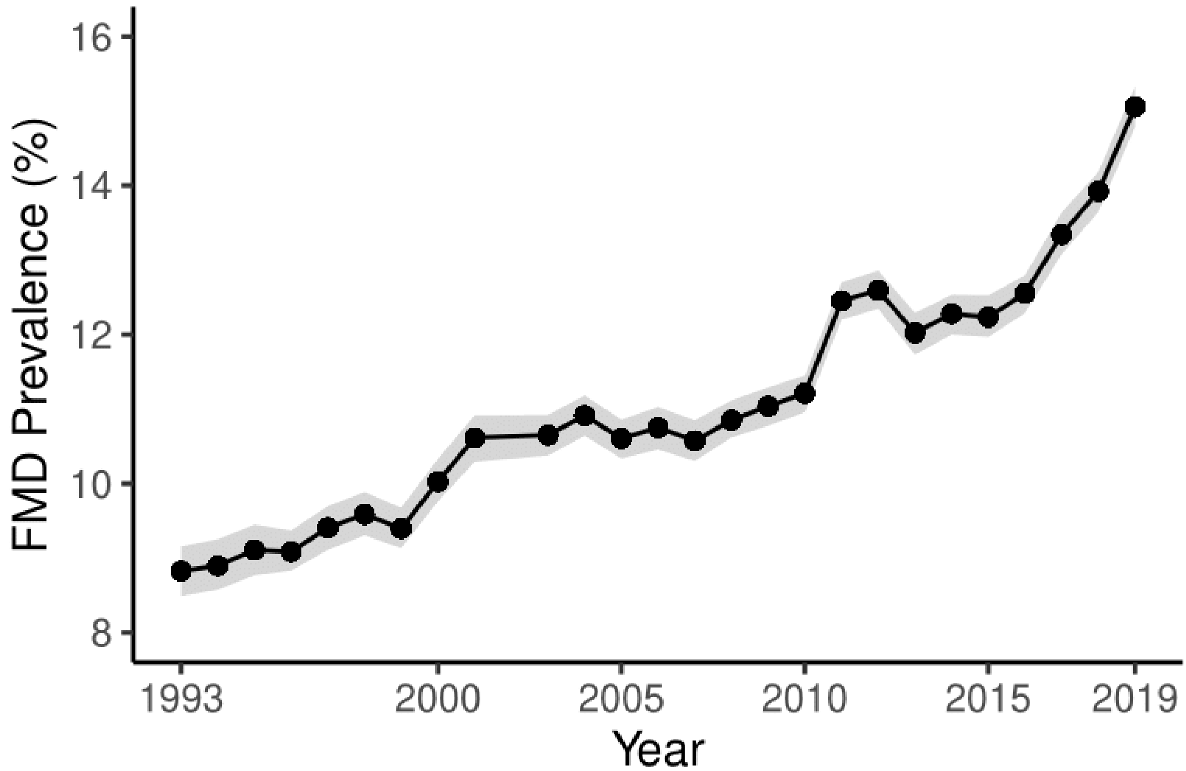
Finally, statistical explanations for our observed trends include our use of age-standardization and the mathematical bounding of inequality measures. With an ageing population, our age-standardization upweighted older individuals pre-2000 who reported less FMD and younger individuals post-2000 who reported more FMD, making FMD prevalence rises appear steeper. Separately, as FMD prevalence rose over time, our inequity findings will in-part reflect the mathematical bounding of inequality measures instead of substantive changes in the inequitable systems producing social inequities in health. As Houweling *et al.*[80] explain, relative-scale inequality measures tend to become smaller as overall disease prevalence increases while absolute-scale measures tend to become larger as overall disease prevalence approaches 50%.

There are some limitations of our work. First, since BRFSS respondents do not report exact household incomes, our imputation approach for determining poverty could lead to exposure misclassification. Second, due to selection bias our study likely under-counts mental distress among marginalized groups, particularly in recent years. BRFSS excludes incarcerated adults and those experiencing homelessness who are more likely to be socially disadvantaged[130–132] and to experience mental distress.[131,133] We also exclude individuals with missing information on study variables, who are more-often socially disadvantaged. Third, not all intersection-specific trend estimates in our study are equally comparable, as they rely on different sets of unsuppressed annual prevalence estimates. This particularly affects trends for Hispanic Black intersectional populations given five of six have no unsuppressed estimates prior to 2010. Fourth, BRFSS changed its survey methodology in 2011 to incorporate cell-phone interviews and use raking for survey weighting instead of post-stratification.[88] While these changes likely reduce selection bias and were not associated with any discontinuity in reported FMD prevalences, they affect the comparability of FMD prevalence estimates pre- and post-2011. Finally, mental distress may be differentially reported across social populations due to differing cultural conceptions of ‘mental distress’; cultural referencing where respondents judge their own mental health based on the typical health of people in their community;[134–137] self-presentation bias where individuals are less likely to divulge sensitive information if they feel their interviewer may not understand their experiences (e.g., due to having a different presumed sex or race); or cultural stigmatization.[124,138] In most cases, we expect these biases would disproportionately under-count mental distress among minoritized groups.[138–141]

Taken in sum, our findings show that mental distress poses a large and growing burden to population health deserving considerable policy attention. Further, as the absolute inequity in FMD between more and less privileged groups has widened, policy responses should explicitly aim to improve health equity, targeting those intersectional groups most in-need. For these reasons, we expect policies which disproportionately benefit lower-SES women and Black individuals would be especially impactful such as expanding health insurance coverage,[142] improving access to affordable child care,[143] housing,[144] and child tax credits,[145] eliminating work requirements from safety net policies,[146–148] and preventing intimate partner violence.[149] Future inferential research should likewise seek to explain why lower-SES groups have experienced disproportionate rises in mental distress and evaluate the above-mentioned social policies specifically in terms of their effects on mental health equity.

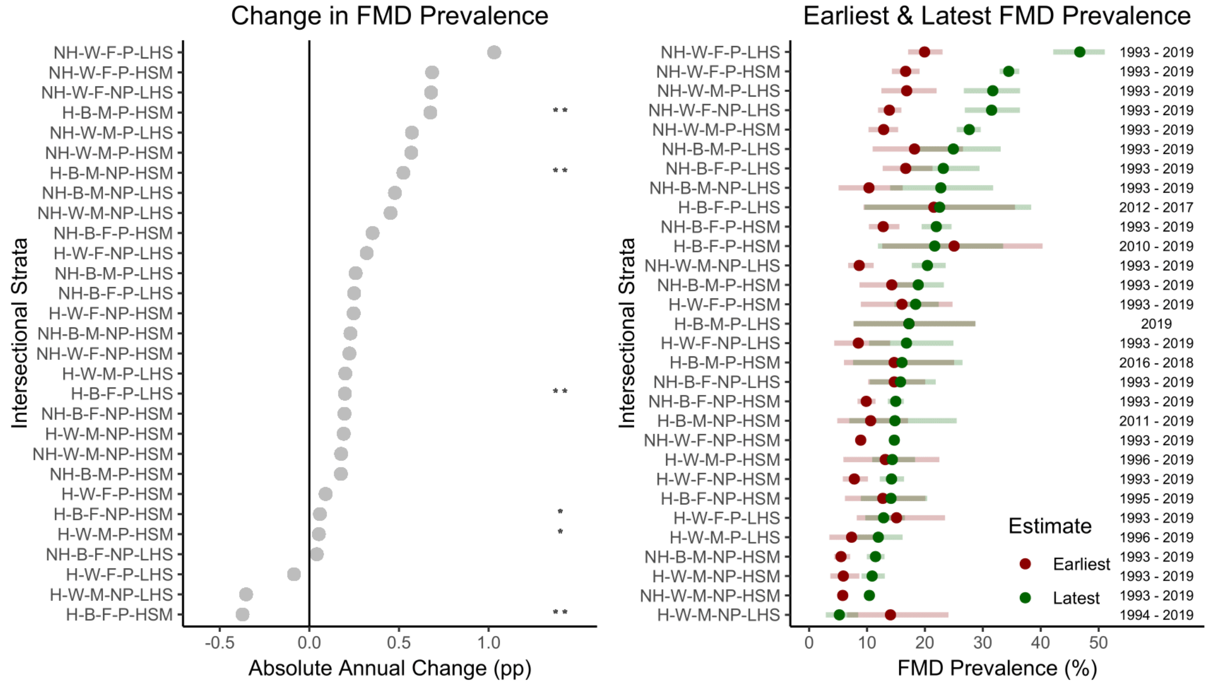
2.6 Relevant Tables and Figures

Figure 2.1. Age-standardized past-month prevalence of FMD between 1993 and 2019 overall, BRFSS 1993-2019.



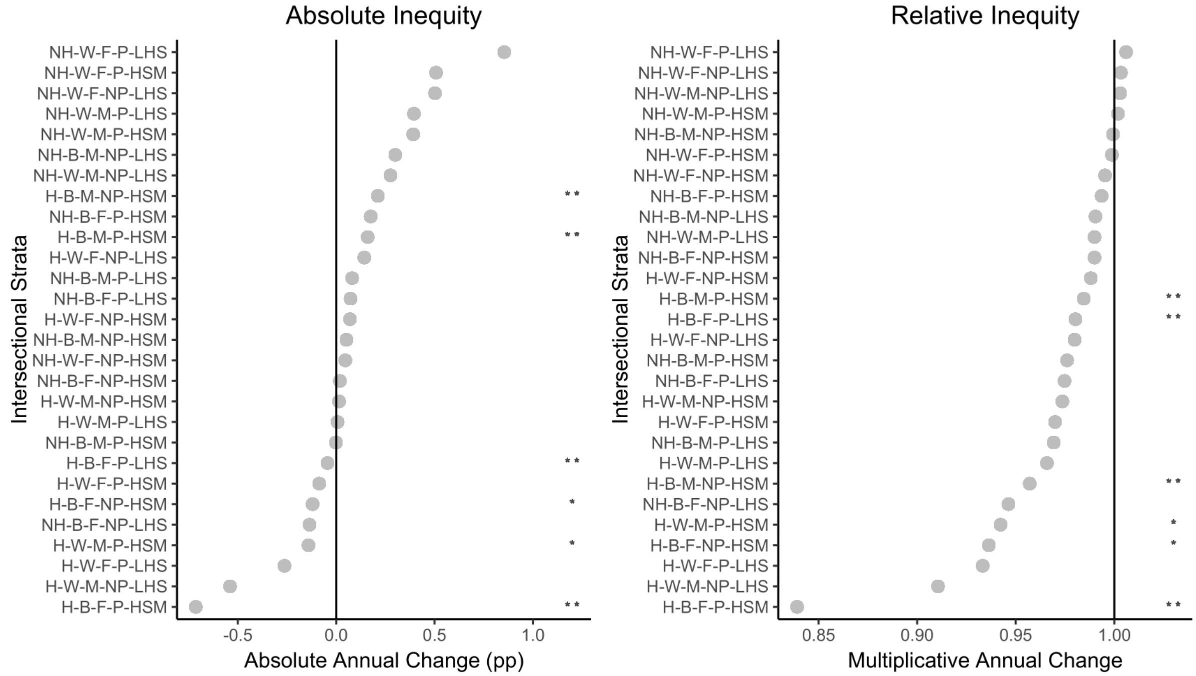
Legend: FMD: Frequent Mental Distress. Shading reflects year-specific estimate 95% confidence intervals.

Figure 2.2. Average annual change in age-standardized FMD prevalence and earliest and latest reported prevalence across intersectional social groups between 1993 and 2019, BRFSS 1993-2019.



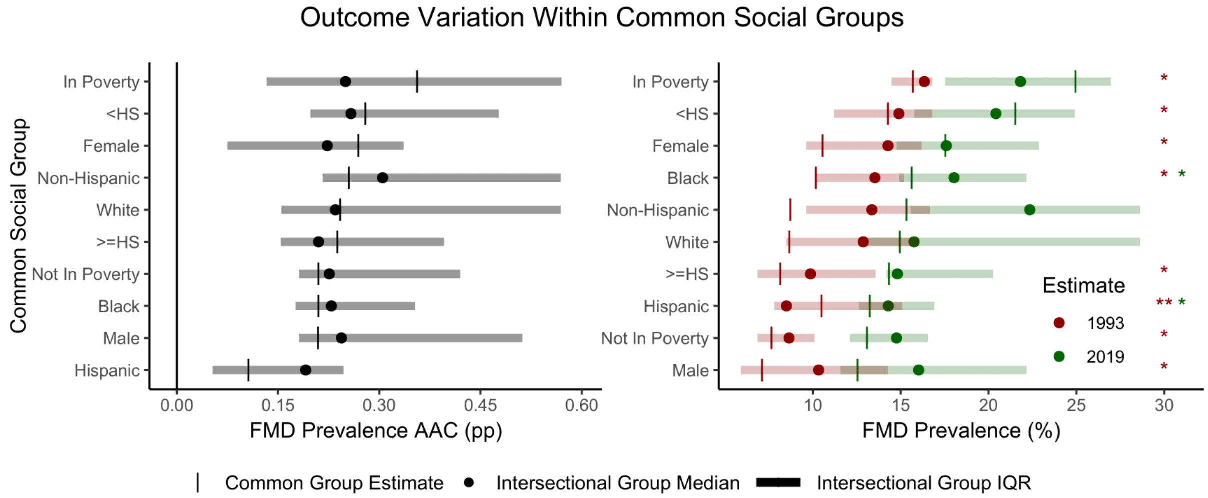
Legend: FMD: Frequent Mental Distress. NH/H: Non-Hispanic/Hispanic. W/B: White/Black. F/M: Female/Male. LHS/HSM: Less than High School Completion/High School Completion or More. NP/P: Not in Poverty/In Poverty. AAC estimates presented in panel A based on fewer than 50% of annual prevalence estimates are marked **, those based on 50-79% are marked *, and those based on at least 80% are unmarked. Year ranges presented in panel B reflect the corresponding years for the earliest and latest group FMD prevalence estimates. Error bars presented in panel B reflect estimate 95% CI.

Figure 2.3. Average change in absolute and relative social inequities in age-standardized FMD prevalence across intersectional social groups between 1993 and 2019, BRFSS 1993-2019.



Legend: FMD: Frequent Mental Distress. NH/H: Non-Hispanic/Hispanic. W/B: White/Black. F/M: Female/Male. LHS/HSM: Less than High School Completion/High School Completion or More. NP/P: Not in Poverty/In Poverty. AAC estimates presented based on fewer than 50% of annual inequity estimates are marked **, those based on 50-79% are marked *, and those based on at least 80% are unmarked. All inequities are defined comparing each social group's annual FMD prevalence to that of those NH-W-M-NP-HSM.

Figure 2.4. Intra-categorical variation in age-standardized FMD prevalences and average annual trends across common social groups between 1993 and 2019, BRFSS 1993-2019.



Legend: FMD: Frequent Mental Distress. AAC: Average Annual Change. HS: High School. pp: percentage-point. Each common social group consists of 16 discrete intersectional subgroups. Common group estimates correspond to all individuals with a given identity (e.g., FMD prevalence among all males), whereas intersectional group median and IQR summarize the distribution of estimates reported across their nested subgroups. Measures based on fewer than 50% of intersectional subgroups (N < 8) are marked **, those based on 50-79% (N = 8-12) are marked *, and those based on at least 80% (N = 13-16) are unmarked. Note: Both less educated Hispanic Black groups not in poverty were entirely suppressed in our analysis, and so are excluded from panels A and B.

Table 2.1. Common social group frequent mental distress summaries between 1993 and 2019, BRFSS 1993-2019.

Social Axis		FMD Prevalence (%, 95% CI)			Absolute Inequity (PD, 95% CI)			Relative Inequity (PR, 95% CI)		
		1993	2019	AAC	1993	2019	AAC	1993	2019	AAC
Presumed Sex	Male	7.1 (6.6 to 7.5)	12.5 (12.1 to 12.9)	+0.21	-	-	-	-	-	-
	Female	10.5 (10.1 to 11.0)	17.5 (17.1 to 18.0)	+0.27	+3.4 (+2.8 to +4.2)	+5.0 (4.4 to 5.6)	+0.06	1.49 (1.37 to 1.62)	1.40 (1.34 to 1.46)	1.00
Self-Identified Race	White	8.7 (8.3 to 9.0)	14.9 (14.7 to 15.3)	+0.24	-	-	-	-	-	-
	Black	10.2 (9.3 to 11.2)	15.6 (14.8 to 16.5)	+0.21	+1.5 (+0.6 to +2.5)	+0.7 (-0.2 to +1.7)	-0.03	1.18 (1.07 to 1.30)	1.05 (0.98 to 1.11)	0.99
Self-Identified Ethnicity	Non-Hispanic	8.7 (8.4 to 9.0)	15.3 (15.0 to 15.6)	+0.26	-	-	-	-	-	-
	Hispanic	10.5 (8.4 to 12.9)	13.2 (12.2 to 14.3)	+0.11	+1.8 (-0.4 to +4.3)	-2.1 (-3.3 to -1.0)	-0.15	1.21 (0.96 to 1.49)	0.86 (0.79 to 0.94)	0.98
Educational Attainment	< HS	14.3 (12.8 to 16.0)	21.5 (20.2 to 22.8)	+0.28	-	-	-	-	-	-
	≥ HS	8.2 (7.8 to 8.5)	14.3 (14.0 to 14.6)	+0.24	+6.1 (+4.7 to +7.8)	+7.2 (+5.9 to +8.5)	+0.04	1.75 (1.56 to 1.97)	1.50 (1.41 to 1.60)	0.99
Household Poverty Status	No	7.6 (7.4 to 7.9)	13.1 (12.8 to 13.4)	+0.21	-	-	-	-	-	-
	Yes	15.7 (14.4 to 17.2)	24.9 (23.9 to 26.0)	+0.36	+8.1 (+6.6 to +9.7)	+11.9 (+10.8 to +12.9)	+0.15	2.06 (1.86 to 2.29)	1.91 (1.81 to 2.00)	1.00

FMD: Frequent Mental Distress. CI: Confidence Interval. PD: Prevalence Difference. PR: Prevalence Ratio. AAC: Average Annual Change. HS: High School.
Note: Relative Inequity AAC estimates reflect the average multiplicative change in inequity magnitude per year, while FMD Prevalence and Absolute Inequity AAC estimates reflect the average absolute change in each outcome per year.

2.7 Relevant Appendices

Appendix 2.A. Comparing Main Study Findings with Evidence Across the Existing Literature, BRFSS 2001-2019.

Conclusion Reached In This Study	Conclusions Reached In The Existing Literature	Summarized Similarities and Differences
Point-in-Time, Cumulative, or General Relationships Observed Concerning The Social Distribution of Mental Distress		
With the exception of Hispanic individuals, less privileged social groups by race, presumed sex, educational attainment, and household poverty status have predominantly experienced greater mental distress than more privileged social groups.	**Intersectionally:** Two intersectional analyses exist examining granular social differences in the US burden of mental distress. Both found predominantly greater mental distress among less privileged groups.[150,151] **Race and Ethnicity:** Whether Black and/or Hispanic groups report more mental distress than those non-Hispanic white varies across the literature. Some studies reporting less mental distress among racially minoritized groups[45,66,67,129,152–155], other reporting more,[70,150,156–159] and some reporting no differences or inconsistent differences across racial or ethnic groups.[43,52,65,71,155,160,161] **Sex:** Women consistently report greater mental distress than men.[40,45,65,71,150,152,159,162–166] **Educational Attainment:** The literature mostly suggests that those less educated report more mental distress.[43,52,65,157,161,163] However, a sizeable literature also suggests that the relationship between educational attainment and mental distress is non-linear,[45,66,67,159] with those reporting 'some college' in particular experiencing high mental distress compared to those with a high school diploma.[45,67,159–161] **Income/Poverty:** Income consistently shows an inverse relationship with mental distress overall and within subgroups defined by sex, race/ethnicity, or sex and race/ethnicity.[43,45,50,52,65,67,71,157,159,167]	Most literature documents similar qualitative relationships between social privilege and mental distress as we do in our study, though with some variation. For example, while the literature is near-unanimous considering sex and income-based inequities in burden and supportive considering granular intersectional inequities in burden, it is more mixed by race and ethnicity and, to an extent, educational attainment.
Longitudinal Trends Observed in the Occurrence of Mental Distress Overall and Across Social Groups		
On an age-standardized basis, the national burden posed by mental distress has increased since the early 1990s, both overall and for the	**Overall:** For most studies examining trends in mental distress over time periods overlapping with our study, mental distress burden increased over time.[40,43–45,63,65,66,168] Mojtabai & Jorm,[69] however, only reported increases for one of three negative mental health outcomes (number of mentally unhealthy days, but not depressive symptoms or non-specific psychological distress), while Olfson *et al.*[70] reported declining prevalence of serious psychological distress between 2004/5 and 2014/15.	Consistent with our findings, the majority of studies assessing US trends in mental distress over time-periods overlapping with our study have found rising prevalence over time, both

majority of individually and intersectionally-defined social groups.	**Race and Ethnicity:** Most literature documents rising mental distress over time for all race/ethnicity groups considered in our analysis, though this literature is inconsistent in which groups reported the greatest rises in burden.[8,43,45,63,65,66,71] Olfson *et al.*[70] by contrast report declining serious psychological distress in all racial/ethnic groups. **Sex:** Most literature likewise documents rising mental distress for both men and women with women reporting larger rises in burden,[40,44,45,65] except Evans & Erickson who reported larger increases between 1993 and 2008 among men,[71] Goodwin *et al.* who found comparable increases in anxiety by sex,[43] and Olfson *et al.* who reported declining serious psychological distress for men and women.[70] **Educational Attainment:** Analyses examining mental health trends by education have reached mixed conclusions, with some showing rising mental distress across educational groups,[43,65,67] others showing rises only among the more educated,[45,63,66] and others showing rises only among those less educated[44] or low SES.[168] **Income/Poverty:** Most related analyses have found rising mental distress across income groups,[43,63,65,67,71] except for Weinberger *et al.*[45] who found no clear rise in depression except for those with some college education. Most studies also reported higher increases for those with lower incomes.[63,65,67]	overall and by race and ethnicity, sex, and income. By education, however, the literature is mixed; particularly concerning whether those with less education saw mental distress rise, remain steady, or fall over time.
Over our study period, social inequities in mental distress have widened by household poverty status and narrowed by ethnicity. Time trends for intersectionally-defined inequities have varied across social groups and scales.	**Intersectionally:** To our knowledge, only Peele[66] and Todd and Teitler[44] have explicitly examined trends in intersectional inequities in mental distress over time. Peele examined variation in trends in general mental illness and anxiety by education within non-Hispanic whites, finding broadly similar trends by educational group, while Todd and Teitler examined trends in depression within men and women while also stratifying by either education or income. In each case, they found similar within-sex trends by education and income group. Evans & Erickson[71] conducted a similar study, examining how depressive symptoms varied for intersectional groups while adolescents in 1994-95 and young adults in 2008 while adjusting for age. In their analysis, they found slightly larger increases in depressive symptoms over time for those non-Hispanic Black versus non-Hispanic White, marked improvements for Hispanic populations compared to non-Hispanic populations, and slightly larger mental health declines for women compared to men and those with non-low incomes compared to low incomes. **Race and Ethnicity:** While we consider race- and ethnicity-based inequities separately, all existing studies comparing trends in burden over time categorized race and ethnicity together. With the exception of Evans & Erickson,[71] Goodwin *et al.*,[43] and Olfson *et al.*[70]	Our findings were mostly consistent with prior literature, except concerning race- and sex-based inequities in distress. We found race- and sex-based inequities remained broadly constant over time while most studies found race-based inequities narrowed and sex-based inequities widened.

	for race-based inequities and Ettman *et al.* for ethnicity-based inequities,[65] this literature mostly suggests that race- and ethnicity-based inequities have narrowed over time.[45,63,65–67] **Sex:** Except for Evans & Erickson[71] and Olfson *et al.*[70] the existing literature near-unanimously suggests that sex-based inequities are widening due to larger increases in burden for women.[43–45,63,65,67] Estimates from the Institute of Health Metrics and Evaluation (IHME) support inequities widening or remaining constant based on the specific mental health outcome considered.[40] **Educational Attainment:** The literature is mixed concerning trends in education-based inequities, with some reporting narrowing inequities,[63,65,66] others widening inequities,[43–45] and Goodwin *et al.*[63] reporting no change in inequities. **Income/Poverty:** Finally concerning income or poverty-based inequities in mental distress, findings have been mixed concerning whether inequities between higher- and lower-income groups were widening or narrowing over time.[43,45,63,65,67,70,71]	

Appendix 2.B. Trends in Mental Health and Health Inequities Across Asian, Native American or Alaska Native, and Native Hawaiian or Pacific Islander Populations, BRFSS 2001-2019.

Study Population and Suppressed Estimates

Consistent with OBM minimum reporting standards at the time, ‘Asian’ and ‘Native Hawaiian or Pacific Islander’ (NHPI) racial identities were not disaggregated in BRFSS prior to 2001. For this reason, we restrict our supplemental analysis to 2001-2019 where groups could be assessed separately. We also restrict our intersectional analyses to three-way stratifications by race, presumed sex, and household poverty status as more granular analyses resulted in many intersectional groups being fully suppressed.

Our supplemental analysis population consisted of 264,934 respondents, with annual samples ranging from 7382 in 2001 to 19,085 in 2017 with a median of 15,697. Racially, 45% of this population self-identified as Asian, 45% as NAAN, and 10% as NHPI. Considering other demographic characteristics, 54% were presumed female, 22% were living in household poverty, 9.8% had less than high school completion, and 8.8% self-identified as Hispanic. Intersectional groups defined by race, presumed sex, and household poverty status ranged in size from 2948 respondents (for those NHPI, male, and in poverty) to 52,962 (for those Asian, female, and not in poverty). Sociodemographic characteristics stratifying by race indicate that all groups were predominantly female, non-Hispanic, more educated, and not living in household poverty. Compared to our primary analysis population, all groups were comparably female and more likely to be living in household poverty (Primary Population: 10% In Poverty), those NAAN and NHPI were more-often Hispanic (Primary Population: 4.3% Hispanic), and those NHPI and Asian were respectively more and less likely to have less than high school completion (Primary Population: 7.7% <HS).

Appendix 2.B Table 1: Characteristics of Supplemental Analysis Population

Demographic Characteristics	Racial Group		
	Asian	NAAN	NHPI
N (%)	119,489 (45)	118,009 (45)	27,436 (10)
Presumed Sex: Female – N (%)	61,679 (52)	66,185 (56)	15,222 (56)
Ethnicity: Hispanic – N (%)	3889 (3)	15,756 (13)	3697 (14)
Education: Less than HS – N (%)	4193 (4)	19,782 (17)	2116 (8)
Household Status: In Poverty – N (%)	15,773 (13)	34,519 (29)	7330 (27)
Pooled Intersectional N – [Min, Max]	[7062, 52,962]	[13,375, 45,041]	[2948, 10,838]

HS: High School. NAAN: Native American or Alaska Native. NHPI: Native Hawaiian or Pacific Islander. N and (%) are unweighted, reflecting BRFSS sample characteristics. Percentages reflect column totals. Intersectional N jointly stratify by race, presumed sex, and household poverty status.

Data suppression was generally low across one, two, and three-way stratifications and was concentrated early in the 2001-2019 analytic period. No year-specific FMD prevalence estimates were suppressed for any racial population overall though 18% of estimates (N=39 of 216) were suppressed for intersectional groups defined jointly by race, presumed sex, and household poverty status. Across these intersectional groups, no population estimates were suppressed for those NAAN, 28% (N=5) and 17% (N=3) of estimates were suppressed for Asian men and women in poverty, and between 11% (N=2) and 67% (N=12) of estimates were suppressed for NHPI groups, with suppression across racial groups predominantly for populations in poverty (N=4 of 6, 67%).

Trends Across Racial Groups Overall

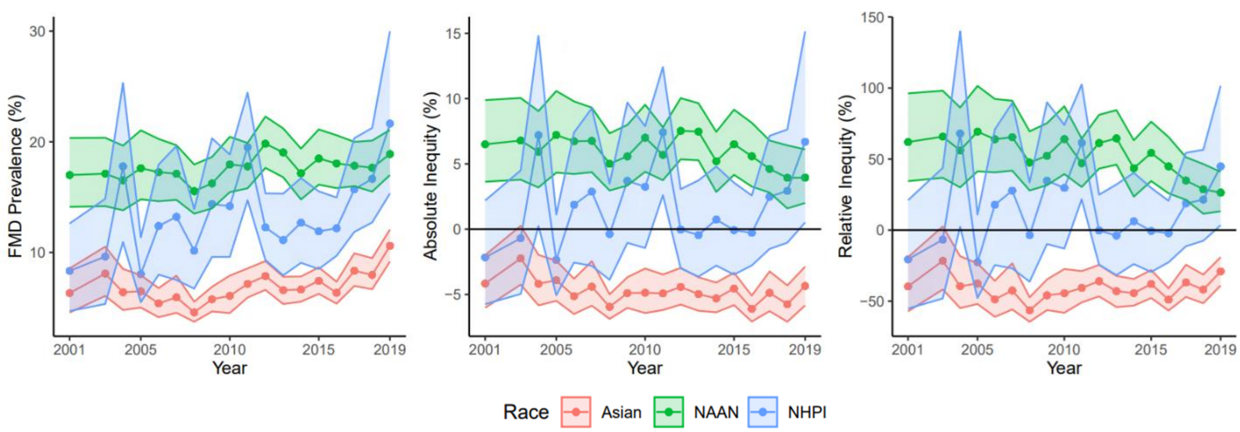
FMD Prevalence

Between 2001 and 2019, age-standardized FMD prevalence increased for all racial groups assessed in our supplemental analyses, with the smallest and largest rises in prevalence for those NAAN (Absolute: +1.9%, Relative: +11%) and NHPI (Absolute: +13.3%, Relative: +159%). Expressed in terms of the absolute average annual change (AAC) in prevalence, those NAAN saw prevalence increased by +0.11 percentage-points (pp) per year, those Asian by +0.24pp per year, and those NHPI by +0.74pp per year. At all times, those self-identifying as Asian reported the lowest FMD prevalence (2019 FMD Prevalence, 95% CI: 10.6%, 9.2% to 12.1%), while NAAN and NHPI groups did not consistently differ in their reported prevalence.

Social Inequities in FMD Prevalence

Compared to those self-identifying as White, between 2001 and 2019 those Asian have reported consistently lower age-standardized FMD prevalence, those NAAN have reported consistently higher age-standardized prevalence, and those NHPI have not shown any consistent difference in prevalence (Appendix 2.B Fig. 1). Summarizing trends in these inequities over time, Asians have saw their difference in prevalence remain broadly unchanged in absolute and relative terms (AAC: -0.01pp absolutely, 1.00 relatively), while those NAAN have saw their inequity narrow on both scales (AAC: -0.14pp absolutely, 0.98 relatively). For those NHPI inequities have changed erratically over time, though on average have significantly widened in absolute terms while narrowing relatively (AAC: +0.49pp absolutely, 0.98 relatively).

Appendix 2.B Figure 1: Trends in Age-Standardized FMD Prevalence and Social Inequities in FMD Prevalence by Race Compared to Those White, BRFSS 2001-2019.



FMD: Frequent Mental Distress. NAAN: Native American or Alaska Native. NHPI: Native Hawaiian or Pacific Islander. Absolute and Relative Inequities compare year-specific FMD prevalence to those White.

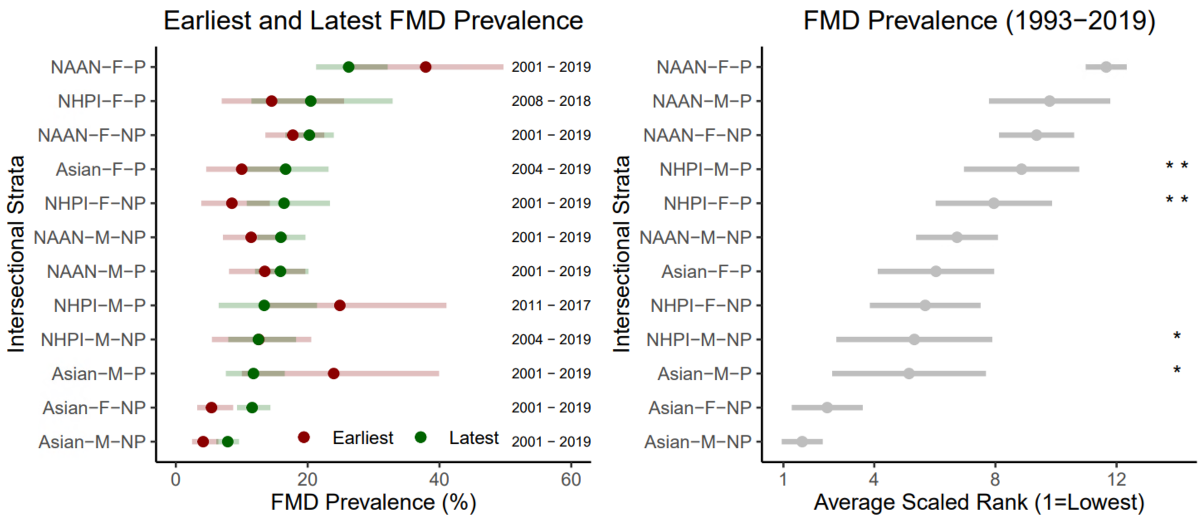
Trends Across Intersectional Groups

FMD Prevalence

Across intersectional groups defined by respondent race, sex, and household poverty status, age-standardized FMD prevalence increased on average between 2001 and 2019 for 66% of groups (N=8 of 12), with most groups reporting falling prevalence either living in household poverty (N=3 of 4) or male (N=3 of 4) (Appendix 2.B Fig. 2, Fig. 3). Of note, NHPI men and women living in household poverty respectively saw the largest declines (AAC: -1.91pp) and rises (AAC: +0.59pp) in prevalence across intersectional groups, though the comparability of their average change estimates with other groups is limited by the narrower time-period over which they have unsuppressed estimates (NHPI men in poverty: 2011-2017, NHPI women in poverty: 2008-2018).

Summarizing the relative burden of age-standardized FMD prevalence experienced by each intersectional group between 2001 and 2019, we observe that those Asian, male and not living in poverty consistently reported the lowest prevalence between 2001 and 2019, while those NAAN, female, and living in poverty consistently reported the highest prevalence (Appendix 2.B Fig. 2). More broadly, the three groups reporting the lowest prevalence were all Asian, while those reporting the highest prevalence were all NAAN.

Appendix 2.B Figure 2: Average age-standardized FMD prevalence rank and earliest and latest age-standardized FMD prevalence of intersectional social groups between 1993 and 2019, BRFSS.



FMD: Frequent Mental Distress. NAAN: Native American or Alaska Native. NHPI: Native Hawaiian or Pacific Islander. M/F: Male/Female. NP/P: Not in Poverty/Poverty. Left Panel: Year ranges reflect the corresponding years for earliest and latest FMD prevalence estimates. Error bars reflect 95% Confidence Intervals. Right Panel: Averages are based on at least 80% of possible annual prevalence estimates unless otherwise marked via * or **. Averages marked * are based on between 50-79% of possible estimates, while averages marked ** are based on fewer than 50% of possible estimates. Error bars reflect ±1 standard deviation of group-specific unsuppressed annual prevalence ranks.

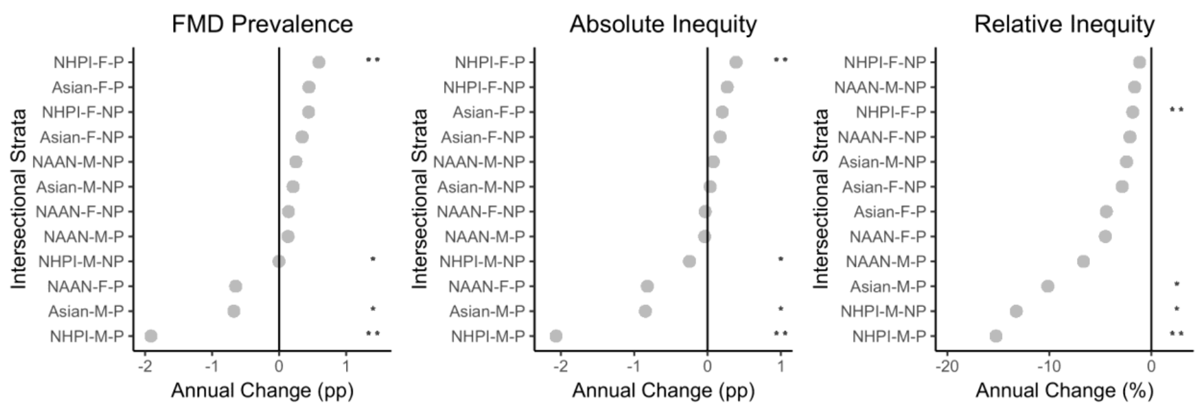
As a higher-than-average proportion of NAAN individuals are Hispanic, we additionally examined trends for this racial group stratifying by ethnicity. From this analysis, Hispanic and non-Hispanic NAAN individuals reported similar age-standardized FMD prevalence in 2001 (FMD Prevalence, 95% CI: Non-Hispanic – 17.4%, 14.6% to 20.4%. Hispanic – 16.1%, 10.1% to 23.2%), though over time those non-Hispanic have saw FMD prevalence rise (AAC: +0.23pp, 2001-2019 Difference: +4.1%), while those Hispanic have saw prevalence fall (AAC: -0.06pp, 2001-2019 Difference: -1.2%).

Social Inequities in FMD Prevalence

We observe that, defined in contrast to those White, male, and not in poverty, social inequities in FMD changed varyingly in absolute terms over time and improved for all groups in relative terms (Appendix 2.B Fig. 3).

Comparing trends in inequities for Hispanic and non-Hispanic NAAN populations compared to those non-Hispanic and White, we observe that over time social inequities in FMD for those Hispanic and NAAN have disappeared on both scales (2019 Inequity, 95% CI: Absolute – -0.4%, -3.2% to 3.2%. Relative – -2.3%, -21% to +21%). At the same time, inequities for those non-Hispanic and NAAN have narrowed marginally in absolute terms and to a greater extent in relative terms (2019 Inequity, 95% CI: Absolute – 6.2%, 3.8% to 9.1%. Relative – +41%, +25% to 59%).

Appendix 2.B Figure 3: Trends in Age-Standardized FMD Prevalence and Social Inequities in FMD Prevalence Across Intersectional Groups, BRFSS 2001-2019.



FMD: Frequent Mental Distress. NAAN: Native American or Alaska Native. NHPI: Native Hawaiian or Pacific Islander. M/F: Male/Female. NP/P: Not in Poverty/In Poverty. Pp: percentage-point. Averages are based on at least 80% of possible annual prevalence estimates unless otherwise marked via * or **. Averages marked * are based on between 50-79% of possible estimates, while averages marked ** are based on fewer than 50% of possible estimates. Note: Inequities are defined in contrast to those white, male, and not in poverty whose average annual change in FMD prevalence was +0.17pp.

Appendix 2.C. Comparing BRFSS and NCHS data suppression approaches and the percentage of year-specific FMD prevalence estimates suppressed by intersectional stratifications between 1993 and 2019 under each approach, BRFSS 2001-2019.

Comparing BRFSS and NCHS Data Suppression Approaches

BRFSS recommendations for when to mask proportion estimates differ somewhat on a state-by-state and annual basis, reflecting the state administration of BRFSS and continued development of its methodology. In most cases, however, BRFSS recommendations have been to suppress estimates where either: 1) the proportion denominator (i.e. population sample size) is less than 50, or 2) the relative standard error (RSE) of an estimate is >30%.[169] By contrast, current NCHS guidelines recommend masking proportion estimates where: 1) the effective sample size n_e contributing to an estimate accounting for design effects is less than 30, with

$$n_e = \frac{Sample\ Size}{Design\ Effect} = \frac{n}{\frac{\widehat{var}(\hat{p})}{\hat{p}(1-\hat{p})/n}} = \frac{\hat{p}(1-\hat{p})}{\widehat{var}(\hat{p})},$$

where $\hat{p}$ is the point-estimated FMD prevalence as a proportion; 2) either no-one or everyone in a population reports FMD (i.e. $\hat{p}$ equals 0 or 1); 3) the absolute width of an estimate's 95% confidence interval (CI) is more than 30% (i.e. upper 95% CI– lower 95% CI > 0.3); or 4) the absolute width of an estimate's 95% CI is more than 130% the size of the estimate itself (i.e. absolute 95% CI width divided by $\hat{p}$ is >1.3).[100]

The Extent of Data Suppression applying BRFSS and NCHS Suppression Guidelines

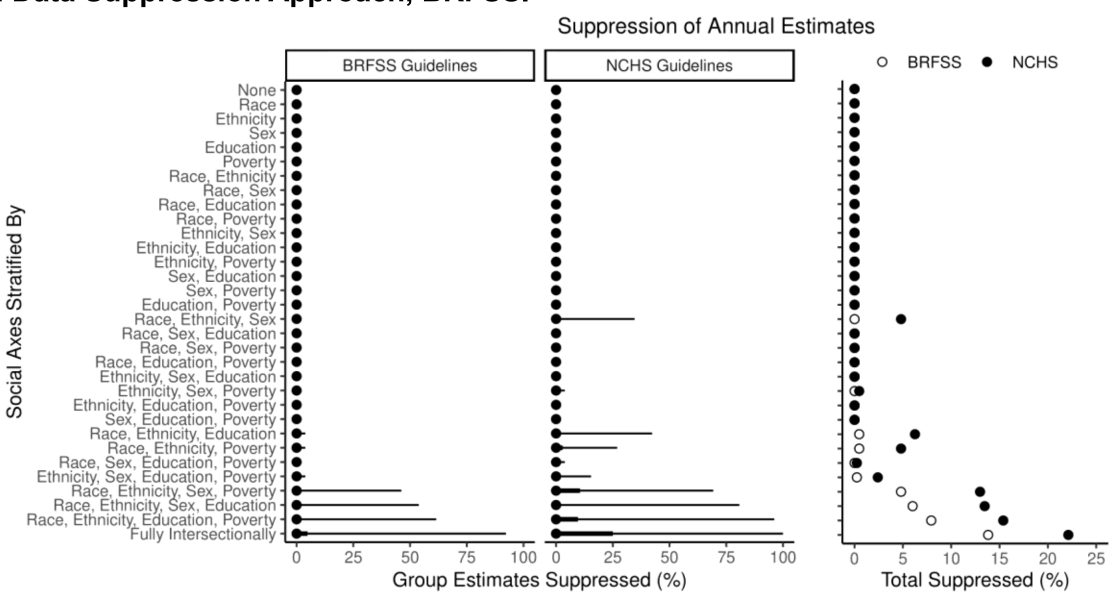
Data suppression was generally low across most levels of stratification, concentrated early in our study period, and more extensive under NCHS suppression guidelines. Under NCHS guidelines, no year-specific FMD prevalence estimates were suppressed for the whole population or common social gorups, while 22% of estimates (N=184 of 832) were suppressed for intersectional groups defined jointly by race, ethnicity, presumed sex, educational attainment, and household poverty status (Appendix 2.C Table 1, Fig. 1). Across these intersectional strata, 18 of 32 groups (56%) had no estimates suppressed, while 24 of 32 groups (75%) had fewer than a quarter of estimates suppressed. The majority of suppressed estimates for intersectional groups (N=168, 91%) were for those Hispanic, less educated, and not living in household poverty, with two groups in particular (Black Hispanic men and women with less than high school completion and not living in household poverty) having their estimates suppressed for all study years (N=52, 29% of all suppressed estimates).

Appendix 2.C Table 1: Extent of Data Suppression Across Levels of Stratification Under Each Data Suppression Approach, BRFSS.

Suppression Method	% Range of Strata Estimates Suppressed by Stratifications				
	1-Axis	2-Axis	3-Axis	4-Axis	5-Axis
BRFSS	0	0	0, 0.5	0, 7.9	13.8
NCHS	0	0	0, 6.3	0.2, 15.4	22.1

BRFSS: Behavioral Risk Factor Surveillance System. NCHS: National Center for Health Statistics.

Appendix 2.C Figure 1: Extent of Data Suppression Across Levels of Stratification Under Each Data Suppression Approach, BRFSS.



‘Fully Intersectionally’ refers to estimates stratifying jointly by self-identified race, ethnicity, presumed sex, educational attainment, and household poverty status. In left and middle panels, points reflect the median group-specific percentage of estimates suppressed, thick lines reflect the IQR of group-specific percentages suppressed, and thin lines reflect the minimum and maximum group-specific percentages suppressed.

Appendix 2.D. Intersectional Social Population Characteristics, BRFSS 2001-2019.

Table 1: Intersectional Social Population Characteristics, BRFSS 1993 – 2019

Intersectional Population	Sample N (% sample / % weighted) [a]			Unsuppressed Annual Estimates		Mentally Unhealthy Days – Median [IQR] [a]		FMD Prevalence (%) (95% CI) [a]	
	Overall	1993	2019	N	Range	1993	2019	1993	2019
NH-W-M-P-LHS	30,536 (0.5 / 0.7)	872 (1.0 / 0.9)	1340 (0.5 / 0.7)	26	1993-2019	0 [0, 3.6]	1.9 [0. 19.5]	16.8 (12.5 to 22.0)	31.7 (26.7 to 36.4)
NH-W-M-P-HSM	113,104 (1.8 / 2.3)	1850 (2.1 / 2.9)	6827 (2.4 / 2.5)	26	1993-2019	0 [0, 4.7]	2.0 [0, 14.9]	12.9 (10.2 to 15.4)	27.6 (25.5 to 29.6)
NH-W-M-NP-LHS	123,098 (1.9 / 2.3)	2853 (3.3 / 3.0)	3865 (1.3 / 2.2)	26	1993-2019	0 [0, 2.0]	0 [0, 7.8]	8.6 (6.7 to 11.1)	20.4 (17.7 to 23.6)
NH-W-M-NP-HSM	2,094,316 (32.8 / 33.3)	26,933 (31.1 / 35.0)	106,232 (36.6 / 31.3)	26	1993-2019	0 [0, 1.3]	0 [0, 3.0]	5.8 (5.4 to 6.3)	10.4 (10.0 to 10.8)
NH-W-F-P-LHS	59,307 (0.9 / 0.9)	2008 (2.4 / 1.5)	1785 (0.6 / 0.8)	26	1993-2019	0 [0, 7.2]	9.7 [0, 29.9]	19.9 (17.1 to 23.0)	46.7 (32.2 to 51.1)
NH-W-F-P-HSM	227,724 (3.6 / 3.2)	4027 (4.7 / 4.2)	11,146 (3.8 / 3.7)	26	1993-2019	0.8 [0, 5.8]	5.0 [0, 19.2]	16.7 (14.3 to 19.1)	34.5 (32.9 to 36.3)
NH-W-F-NP-LHS	140,315 (2.2 / 1.8)	3223 (3.7 / 2.4)	3050 (1.1 / 1.1)	26	1993-2019	0 [0, 4.4]	2.6 [0, 15.3]	13.9 (11.9 to 15.9)	31.5 (26.9 to 36.4)
NH-W-F-NP-HSM	2,757,936 (43.2 / 32.4)	32,275 (37.3 / 33.6)	116,281 (40.1 / 29.9)	26	1993-2019	0 [0, 3.0]	0 [0, 5.0]	8.9 (8.4 to 9.4)	14.7 (14.2 to 15.2)
NH-B-M-P-LHS	9914 (0.2 / 0.3)	253 (0.3 / 0.3)	469 (0.2 / 0.4)	24	1993-2019	0 [0, 4.5]	0.6 [0, 13.1]	18.2 (11.0 to 26.6)	24.9 (17.7 to 33.1)
NH-B-M-P-HSM	24,924 (0.4 / 0.8)	405 (0.5 / 0.7)	1473 (0.5 / 1.0)	26	1993-2019	0 [0, 4.0]	0 [0, 6.8]	14.3 (8.7 to 19.3)	18.8 (15.0 to 23.3)
NH-B-M-NP-LHS	17,149 (0.3 / 0.4)	399 (0.5 / 0.4)	576 (0.2 / 0.4)	26	1993-2019	0 [0, 1.4]	0 [0, 11.3]	10.3 (5.1 to 16.1)	22.7 (14.0 to 31.8)
NH-B-M-NP-HSM	142,954 (2.2 / 4.0)	2332 (2.7 / 3.1)	7422 (2.6 / 4.8)	26	1993-2019	0 [0, 1.2]	0 [0, 2.6]	5.5 (4.3 to 7.1)	11.5 (10.0 to 13.0)
NH-B-F-P-LHS	23,630 (0.4 / 0.4)	726 (0.8 / 0.6)	700 (0.2 / 0.4)	26	1993-2019	0 [0, 5.8]	1.8 [0, 11.1]	16.7 (12.7 to 21.3)	23.2 (17.4 to 29.4)
NH-B-F-P-HSM	68,919 (1.1 / 1.4)	1152 (1.3 / 1.3)	3140 (1.1 / 1.9)	26	1993-2019	0 [0, 4.5]	1.6 [0., 10.0]	12.8 (10.3 to 15.6)	22.0 (19.4 to 24.6)
NH-B-F-NP-LHS	23,899 (0.4 / 0.3)	533 (0.6 / 0.4)	561 (0.2 / 0.3)	26	1993-2019	0 [0, 4.2]	1.1 [0, 6.1]	14.7 (10.2 to 20.0)	15.8 (10.5 to 21.9)

NH-B-F-NP-HSM	251,580 (3.9 / 4.5)	3276 (3.8 / 3.2)	10,719 (3.7 / 5.2)	26	1993-2019	0 [0, 3.0]	0 [0, 5.0]	9.9 (8.4 to 11.5)	15.0 (13.6 to 16.3)
H-W-M-P-LHS	11,585 (0.2 / 0.9)	123 (0.1 / 0.6)	726 (0.3 / 1.0)	22	1996-2019	-	0 [0, 1.4]	-	11.9 (8.4 to 16.1)
H-W-M-P-HSM	12,466 (0.2 / 0.8)	160 (0.2 / 0.6)	882 (0.3 / 0.9)	20	1996-2019	-	0 [0, 4.8]	-	14.4 (10.9 to 18.3)
H-W-M-NP-LHS	12,818 (0.2 / 0.7)	147 (0.2 / 0.3)	565 (0.2 / 0.8)	24	1994-2019	-	0 [0, 0.3]	-	5.2 (2.9 to 8.5)
H-W-M-NP-HSM	66,745 (1.1 / 2.6)	884 (1.0 / 1.8)	3898 (1.3 / 3.4)	26	1993-2019	0 [0, 1.5]	0 [0, 2.6]	5.9 (3.7 to 8.7)	10.9 (9.0 to 13.1)
H-W-F-P-LHS	22,546 (0.4 / 1.1)	207 (0.2 / 0.5)	1075 (0.4 / 1.4)	25	1993-2019	0.3 [0, 4.6]	0 [0, 2.3]	15.1 (8.2 to 23.5)	12.9 (9.7 to 16.5)
H-W-F-P-HSM	26,346 (0.4 / 1.1)	244 (0.3 / 0.5)	1607 (0.6 / 1.7)	26	1993-2019	0.4 [0, 5.5]	0.2 [0, 7.5]	16.0 (8.9 to 24.8)	18.4 (14.7 to 22.4)
H-W-F-NP-LHS	14,697 (0.2 / 0.5)	159 (0.2 / 0.2)	469 (0.2 / 0.4)	25	1993-2019	0 [0, 2.1]	0 [0, 5.1]	8.5 (4.3 to 14.0)	16.8 (10.4 to 24.9)
H-W-F-NP-HSM	87,978 (1.4 / 2.4)	1017 (1.2 / 1.6)	4255 (1.5 / 3.0)	26	1993-2019	0 [0, 3.5]	0.2 [0, 5.6]	7.8 (5.8 to 10.1)	14.2 (12.2 to 16.4)
H-B-M-P-LHS	1078 (0.02 / 0.1)	7 (0.01 / 0.02)	66 (0.02 / 0.1)	1	2019	-	0.5 [0, 6.9]	-	17.2 (7.7 to 28.7)
H-B-M-P-HSM	1313 (0.02 / 0.1)	29 (0.03 / 0.1)	100 (0.03 / 0.1)	2	2016-2018	-	-	-	-
H-B-M-NP-LHS	1001 (0.02 / 0.05)	18 (0.02 / 0.03)	50 (0.02 / 0.1)	0	-	-	-	-	-
H-B-M-NP-HSM	4188 (0.1 / 0.2)	99 (0.1 / 0.1)	266 (0.1 / 0.3)	7	2011-2019	-	0.1 [0, 4.1]	-	14.8 (6.9 to 25.5)
H-B-F-P-LHS	1313 (0.02 / 0.1)	30 (0.03 / 0.04)	61 (0.02 / 0.1)	3	2012-2017	-	-	-	-
H-B-F-P-HSM	2278 (0.04 / 0.1)	57 (0.1 / 0.1)	133 (0.05 / 0.1)	9	2010-2019	-	2.8 [0, 11.8]	-	21.7 (11.9 to 33.5)
H-B-F-NP-LHS	782 (0.01 / 0.02)	23 (0.03 / 0.02)	19 (0.01 / 0.02)	0	-	-	-	-	-
H-B-F-NP-HSM	5736 (0.1 / 0.2)	149 (0.2 / 0.1)	323 (0.1 / 0.3)	18	1995-2019	-	0.9 [0, 5.9]	-	14.1 (8.9 to 20.4)

FMD: Frequent Mental Distress. NH/H: Non-Hispanic/Hispanic. W/B: White/Black. F/M: Female/Male. LHS/HSM: Less than High School Completion/High School Completion or More. NP/P: Not Living in Household Poverty/Living in Household Poverty. IQR: Inter-Quartile Range. CI: Confidence Interval. [a] Estimates presented reflect the average estimate across bootstrap resamples.

Appendix 2.E. Trends in Population Mental Health Stratifying by Age, BRFSS 1993-2019.

Summarizing Cross-Sectional Differences and Longitudinal Trends by Age

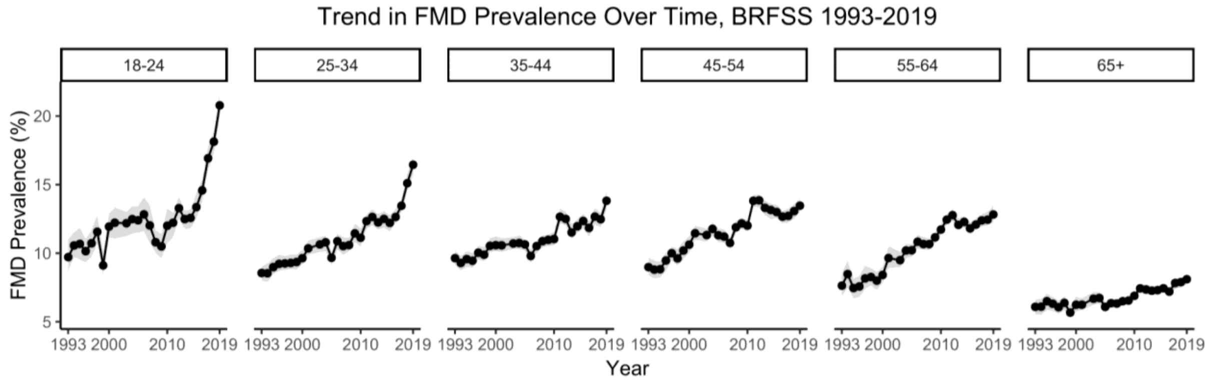
Age cohorts became less similar in their age-standardized FMD prevalences throughout our study period, with cohort-specific FMD prevalences varying by up to 3.6% in 1993 (Range: 6.1%, 9.7%) and 12.7% in 2019 (Range: 8.1%, 20.8%) (Appendix 2.E Table 1). Throughout our study period, those 65 or older consistently reported the lowest FMD prevalences. Those 18-64 years old by contrast reported similar FMD prevalence in 1993 but increasingly divergent FMD prevalence over time, with those 18-24 and 25-34 years old reporting the highest and second highest FMD prevalences in 2019 respectively, and those 35-64 reporting similar FMD prevalences. Between 1993 and 2019, all age cohorts reported rising FMD prevalence (Appendix 2.E Fig. 1), with average annual changes in FMD prevalences across cohorts ranging from +0.08 percentage-points (pp) for those 65+ to +0.43pp for those 18-24 years old and absolute differences ranging from +2.0% to +11.1% for the same groups. Of note, those 18-24 years old and to a lesser-extent 25-34 reported markedly steeper increases from 2015 onwards.

Appendix 2.E Table 1: Age-Standardized FMD Summaries by Age, BRFSS 1993-2019.

Age Group (years)	Annual FMD Prevalence (%, 95% CI)		FMD Prevalence Trends (%)	
	1993	2019	Δ (1993-2019)	AAC
All	**8.5 (8.3 to 8.8)**	**13.7 (13.4 to 14.0)**	**+5.1**	**+0.20**
18-24	9.7 (8.7 to 11.0)	20.8 (20.0 to 21.7)	+11.1	+0.43
25-34	8.6 (8.0 to 9.0)	16.5 (15.7 to 17.0)	+7.9	+0.30
35-44	9.6 (9.1 to 10.2)	13.8 (13.2 to 14.5)	+4.2	+0.16
45-54	9.0 (8.4 to 9.7)	13.5 (13.0 to 14.0)	+4.5	+0.17
55-64	7.6 (6.9 to 8.6)	12.8 (12.2 to 13.5)	+5.2	+0.20
65+	6.1 (5.5 to 6.6)	8.1 (7.8 to 8.4)	+2.0	+0.08

FMD: Frequent Mental Distress. CI: Confidence Interval. AAC: Average Annual Change.

Appendix 2.E Figure 1: Trends in Age-Standardized FMD Prevalence by Age, BRFSS 2001-2019.



FMD: Frequent Mental Distress. Shading reflects year-specific estimate 95% confidence intervals. Age is measured in years.

<u>Variation in Age-Specific Longitudinal Trends by Common Social Group</u>

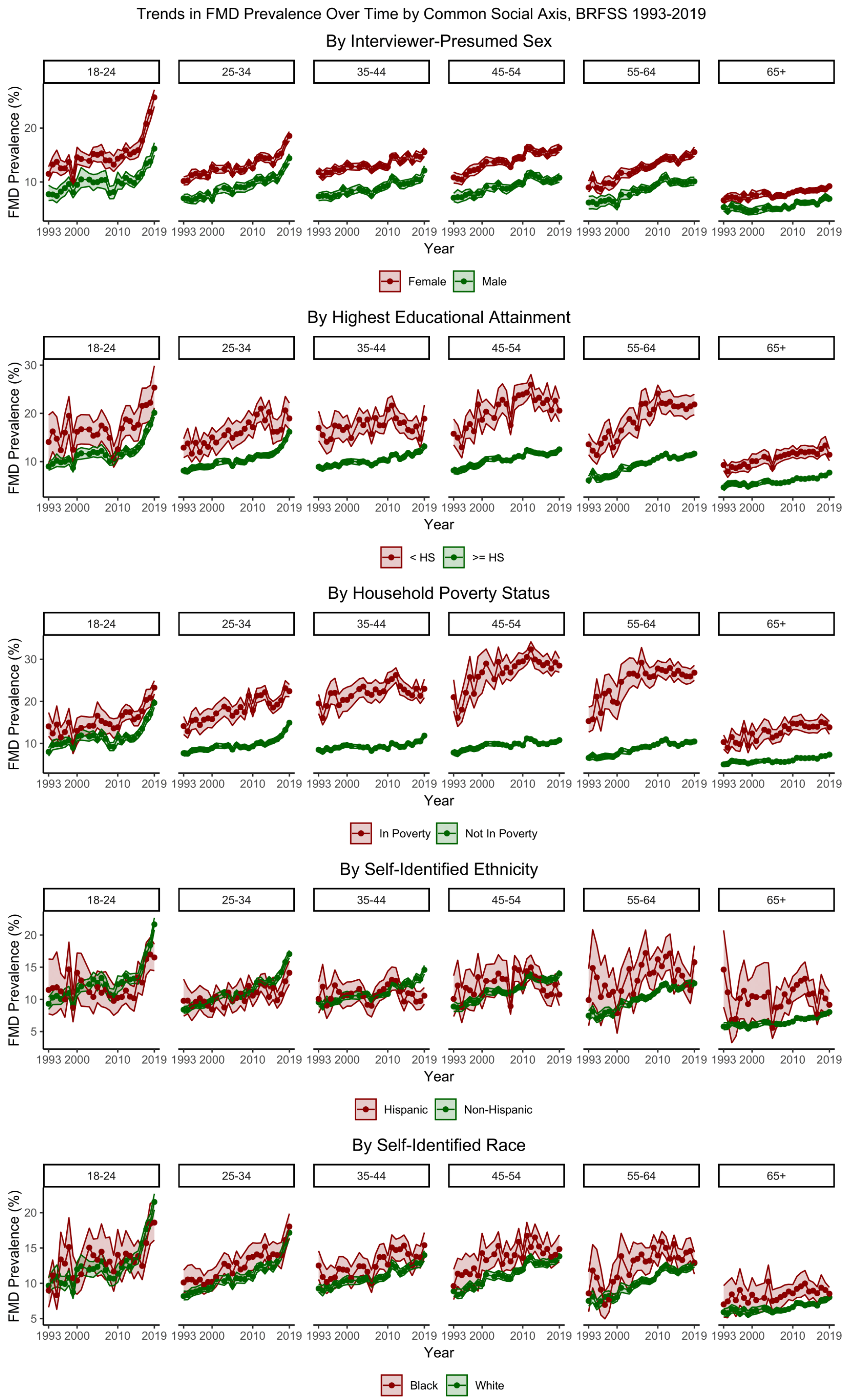
For most common social groups, age-standardized FMD prevalence and trends in FMD prevalence over time were inversely correlated with age. We did, however, observe three unexpected findings comparing different age cohorts of the same social group and the same age cohort across different social groups.

First, trends in age-standardized FMD prevalence for middle-aged populations (i.e. those 45-64 years old) were markedly higher for those less educated or in poverty (i.e. lower socioeconomic status) compared to any other social group. Relatedly, FMD prevalences over most of our study period were highest for middle-aged populations in poverty, despite 18–24-year-olds reporting the highest FMD prevalence and steepest increase in FMD overall.

Second, while FMD prevalence in 2019 was highest for Hispanic and Black populations aged 18-24 years old, the relationship between age and FMD prevalence trends for these social groups is much less prominent.

Finally, while FMD prevalence was consistently higher for less (vs. more) privileged groups defined by sex, educational attainment, and poverty status over time and across age cohorts, this is not the case comparing more and less privileged racial and ethnic groups. In both cases, age-standardized FMD prevalences are similar for Black/White and Hispanic/non-Hispanic groups at age 18-24 years old but diverge as populations age, with FMD prevalence increasing more for less privileged groups.

Appendix 2.E Figure 2: Trends in Age-Standardized FMD Prevalence by Age by Common Social Axis, BRFSS 1993-2019.



FMD: Frequent Mental Distress. HS: High School Completion. Shading reflects year-specific estimate 95% confidence intervals. Age is measured in years.

Chapter 3.

Tax Credits for Greater Equity? Examining The Relationship Between State EITC Policy Availability and Historical Trends in Mental Health and Health Equity.

Tax Credits for Greater Equity? Examining The Relationship Between State EITC Policy Availability and Historical Trends in Mental Health and Health Equity.

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Abstract:

Mental distress has become increasingly common in the United States over recent decades, especially for those in poverty. Cash transfer policies alleviate poverty and have been shown to improve mental health. Using information from the 2000-2019 Behavioral Risk Factor Surveillance System (BRFSS), we assessed whether refundable State Earned Income Tax Credit (EITC) availability has been associated with trends in frequent mental distress (FMD) prevalence and social inequities in FMD over time, generally and among those likely eligible for an EITC. We find refundable State EITC availability is associated with smaller increases in FMD prevalence over time and lower contemporaneous FMD prevalence, particularly among those likely eligible for an EITC and in states where State EITC policies have been implemented longer. State EITC availability is also associated with narrowing sex and poverty-based inequities, widening racial inequities, and higher increases in FMD over time for those in poverty eligible for an EITC.

3.1. Introduction

3.1.1 Trends in Population Mental Health and Health Inequities

Mental distress poses a growing challenge to population health in the United States, with preventable disorders like depression and anxiety increasingly prevalent.[44,45,63,65,66,68,170] These trends also raise concerns over declining social health equity, as most available literature suggests women and those with low and moderate household incomes have seen greater increases in population mental distress over time than men and those with higher household incomes.[44,45,63,65,71,170] For example, in a recent examination of US trends in mental health equity, Blaikie *et al.* show that while social inequities in population mental distress have remained stable since the 1990s by race and to an extent education, they have widened considerably by household poverty status and sex.[170]

To understand why, we aim in this study to assess whether historical and past-year refundable State EITC availability is associated with longitudinal trends in population mental health and health inequities over time. This kind of contextual research is increasingly advocated-for by health equity researchers as a way to understand how social stratification translates into health inequities and identify effective approaches for improving health equity.[14] We focus explicitly on cash transfer policies given the importance of economic resources in explaining health inequities,[171] the disproportionate rise in mental distress among those in poverty, and the possibility of new and expanded cash transfer policies at federal and state levels.

3.1.2 Economic Resources as Determinants of Population Mental Health and Health Inequities

Economic resources such as income and wealth are important intermediate determinants of mental health.[52–55,57,172] They allow individuals to access and make use of health-protecting resources including healthcare, nutritious food, housing, and leisure, and avoid factors harmful to health like stress, low self-esteem and maladaptive coping mechanisms. Economic resources also play a pivotal role in mediating social inequities in mental health, as discriminatory systems like racism and sexism shape who has access to economic resources (e.g., through employment-based discrimination in the hiring process) and whether those resources can effectively be used to improve or protect mental health.[17,54,171,173] For example, a growing literature shows that Black Americans experience fewer health gains from economic resources than white Americans[174–176] due to personal, interpersonal, and structural forms of systemic racism.[174,177,178]

3.1.3 Cash Transfer Policies as Modifiers of Population Mental Health and Health Inequities

Cash transfer policies improve individual access to economic resources by providing individuals with cash or near cash resources (e.g., housing vouchers). As such, they in-theory offer an important means of improving population mental health and health equity. How effectively these policies do so in practice depends on their transfer modality (i.e., whether they provide cash or in-kind benefits), universality (i.e., who is eligible to receive benefits), conditionality (i.e., what those eligible must do to receive benefits), and generosity, as well as the context in which they are administered. For example, in a meta-analysis of randomized controlled trials (RCTs) and lottery studies assessing the mental health impacts of economic transfer policies, Romero *et al.* found that asset transfers and unconditional cash transfers (UCTs) produce greater improvements in mental health than health insurance programs, housing vouchers, and conditional cash transfers (CCTs), with CCTs consistently showing the smallest effects across low- and middle-income countries (LMICs) and high-income countries (HICs).[38] Relatedly, in a meta-analysis of observational studies focusing on social security reforms in HICs, Simpson *et al.* found that in most cases reforms expanding (restricting) the eligibility and generosity of social security policies were associated with improvements (declines) in population mental health and smaller (larger) socioeconomic inequities in mental health.[179]

How these policies impact mental health also appears to depend on whether they change the economic circumstances of recipients. For example, a meta-analysis by Thomson *et al.* found that income changes lifting individuals out of poverty have substantially larger impacts on mental health than other income changes.[57] At the same time, cash transfers which are too small to change recipients' economic circumstances may actually worsen recipient mental health, such as through making them more acutely aware of their financial precarity without offering a means to address it.[180] This has also been proposed as an explanation for why cash transfer recipients in HICs continue to experience worse mental health than non-recipients.[181]

In our study we explicitly focus on State Earned Income Tax Credits (EITC) policies, which are state-administered tax credits provided to working adults with low-to-moderate incomes. These policies mostly follow the same eligibility criteria and payment banding as the Federal EITC policy but vary in their availability, generosity, and refundability within and across states over time. As one of the fastest growing state policy approaches to reducing poverty, understanding how these policies correlate with trends in mental health and health inequities is important to state policymakers and health equity researchers. Evaluating these policies is also worthwhile given they could be expanded in many ways. For example, in 2023, 19 states had no State EITC, four offered a policy worth less than 10% of the Federal EITC, and another four only offered non-refundable credits, which provide no cash benefit to recipients without tax liability. While the mental health effects of these policies have been examined previously,[182–187] no study has examined the association between State EITC policies and longitudinal trends in population mental health. Understanding this relationship is important in its own right when considering population outcomes, since current and future population health and health equity are shaped cumulatively by past events and policies.[188,189]

3.1.4 Aims and Research Questions

We asked two descriptive questions in our study:

1. How have trends in age-standardized frequent mental distress (FMD) prevalence and social inequities in FMD differed comparing states with and without refundable State EITC policies?
2. Have refundable State EITC policies been associated with contemporaneous differences in FMD prevalence and social inequities in FMD at any point over our study period? If so, how has this relationship changed over time?

We answer each question with and without restricting to the subset of individuals most likely eligible to receive a State EITC if one were available.

3.2. Methods

3.2.1 Study Design and Data Sources

We conducted a descriptive, repeated cross-sectional study using EITC policy information from the University of Kentucky Center for Poverty Research (UKCPR) National Welfare Database and survey data from the 2000-2019 Behavioral Risk Factor Surveillance System (BRFSS). BRFSS was established in 1984 by the Centers for Disease Control and Prevention (CDC) to monitor population health and its determinants. It is a set of state-administered, telephone-based health surveys interviewing approximately 400,000 non-institutionalized adults each year across the 50 US states, District of Columbia (DC), Puerto Rico, Guam, and US Virgin Islands. It consists of a core questionnaire administered in all states and module questionnaires administered on a state-by-state and year-by-year basis, each collecting sociodemographic and health information on participants and their households. Through a complex sampling and weighting strategy, BRFSS can be used to provide valid and reliable state and nationally representative estimates of population mental health overall and for key subgroups.[87,88] Since 2011, BRFSS has improved the representativeness of its cohorts by conducted cell-phone interviews as well as landline interviews and through using raking for survey weighting instead of post-stratification.[88]

3.2.2 Sample

Our study population consisted of all BRFSS respondents aged 18-64 years old (i.e., working-age adults), self-identifying as Hispanic and/or Latinx or non-Hispanic White, Black, Asian, or Native American or Alaska Native (NAAN), and with complete information on all study variables: state of residence, age, sex, race, ethnicity, household income, number of adults and dependent children, marital status, and mental health. Participants self-identifying as Native Hawaiian or Pacific Islander (NHPI) were excluded due to small sample sizes while those identifying as non-Hispanic 'Other' were excluded as this grouping aggregates across several unique populations, providing poorly interpretable findings. Those residing in Guam, Puerto Rico, and the US Virgin Islands were excluded as we lack necessary information to determine their household poverty status in the same way as we do for participants residing in the 50 US states and DC (see Section 3.2.3.3.3), while those residing in Colorado, Maine, North Carolina, Oklahoma, and Rhode Island were excluded as these states introduced or eliminated refundable State EITC policies repeatedly throughout our study period (see Section 3.2.4.2, Appendix 3.C Figure 1). We additionally excluded all respondents from 2002 when mental health was not assessed in the core BRFSS questionnaire. An eligibility and inclusion flow diagram for our study population is available in Appendix 3.A.

3.2.3 Measures

3.2.3.1 Outcome Measures

To assess mental health, BRFSS participants were asked the CDC 'health-related quality of life' (HRQOL) question "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?".[89] Participants could respond 0 to 30. This question has good internal validity and test-retest reliability across study populations.[90] Consistent with other BRFSS research, we created an indicator for past-month frequent mental distress (FMD) defined as reporting ≥14 days with poor mental health in the past 30 days,[90] reflecting the symptom period typically used in evaluating clinical depression and anxiety disorders.

3.2.3.2 Exposure Measures

3.2.3.2.1 State EITC Availability

We categorized participants as living in states with or without a funded refundable State EITC policy in the prior tax year using state information from the University of Kentucky Center for Poverty Research (UKCPR) National Welfare Database. We specifically focused on refundable policies – where individuals receive a cash rebate if their total taxes owed are less than the credit they are entitled to – as existing research suggests non-refundable policies do not improve mental health[187] and because individuals eligible for EITCs typically have limited tax liability, meaning they are unlikely to substantially benefit from a non-refundable credit. As in prior research we treat those living in states with non-refundable policies as if their state had no policy.[186]

3.2.3.2.2 Likely Individual Federal and State EITC Eligibility

To identify those most likely to benefit from a State EITC, we also categorize participants separately as likely eligible or ineligible for Federal and State EITC credits based on their age, marital status, number of dependents, and imputed continuous household income using the National Bureau of Economic Research (NBER) TAXSIM 35 tax simulator model.[190] We assumed all married participants filed taxes jointly given EITC credits are unavailable otherwise and only a small minority of married couples choose to file separately.[191] While BRFSS does not directly ask individuals about their EITC receipt, this categorization is analogous to an intent-to-treat (ITT) assignment of likely EITC recipiency.

3.2.3.3 Additional Measures

To better understand the relationship between State EITC policies and the social distribution of FMD, we examined whether the association between State EITCs and FMD prevalence varied by interviewer-presumed sex, collapsed self-reported race and ethnicity, and absolute household poverty status, each defined as below. We also assessed whether State EITC policies were associated with social inequities in FMD defined by each social axis, using those conceptually 'most privileged' under each social axis as referent (i.e., those non-Hispanic white by race and ethnicity, male by sex, and not living in household poverty by income). In doing so, we assume that the population mental health of all disadvantaged groups is made worse relative to what it would be absent the systems of oppression disadvantaging them.

3.2.3.3.1 Presumed Sex

Interviewers are instructed to infer participant sex during their telephone interview based on the sound of the participant's voice, and to only ask participants to self-identify if they cannot presume it confidently. As this is subject to misclassification,[192] we categorized participant sex as 'presumed Male' or 'presumed Female' (hereafter 'male' or 'female' for brevity).

3.2.3.3.2 Race and Ethnicity

Participant race and ethnicity are self-reported separately in BRFSS, though the exact prompt phrasing and available response options have varied over time. To accommodate expected small Hispanic and/or Latinx samples in our study, we collapsed race and ethnicity together for our analysis with categories: (Non-Hispanic) White, Black, Asian, Native American or Alaska Native (NAAN), and Hispanic and/or Latinx (hereafter 'Hispanic' for brevity). We were unable to include Native Hawaiian and Pacific Islander (NHPI) participants in this analysis because of small sample sizes and because they differ from Asian populations in prevalence of mental health conditions[67] and other social, cultural, and economic characteristics.[193] As BRFSS only disaggregated Asian and NHPI response options from 2001 onwards our estimates for the Asian population in 2000 incorporate NHPI individuals, who likely constitute a very small proportion of this annual sample.[194]

3.2.3.3.3 Income and Household Poverty Status

Annual household income is self-reported in BRFSS using discrete bracketed response categories (e.g., $10,000 to $14,999). To determine household poverty status (and likely Federal and State EITC eligibility, see Section 3.2.4.2.2), we first converted these categorical incomes into continuous amounts using the within-category uniform (i.e., random) imputation approach proposed by the State Health Access Data Assistance Center (SHADAC).[94] We chose this approach over alternatives (e.g., mid-point, minimum or maximum-bound imputation) as it performs best at accurately imputing income for those low on the income distribution, where household poverty status and EITC eligibility are determined. To account for uncertainty in each participant's actual household income we repeated this imputation 500 times, using each imputation serially across bootstrap repetitions (see Section 3.2.4.4).

We provisionally based household poverty status on the Census Bureau Official Poverty Measure (OPM),[195] with participants reporting household incomes below the OPM threshold for their household size and number of dependents categorized as 'In Poverty' and otherwise categorized as 'Not In Poverty'. To account for state variation in costs-of-living, we adjusted OPM thresholds prior to determining household poverty status using the Bishaw Index – a Median Rent Index (MRI) based on the ratio of state to national gross median rents.[96,97] We used nominal rent information from the 2000 decennial census and 2002-2019 American Community Survey (ACS), linearly imputing 2001 state rents using 2000 and 2002 figures. To account for inflation not related to housing costs, we adjusted all rents to 2019 dollars using the Bureau of Labor Statistics

Consumer Price Index excluding shelter costs (CPI-LS) before calculating the Bishaw Index by state and year.

3.2.4 Statistical Methods

3.2.4.1 Estimating our Outcomes of Interest

For all study populations each year, we non-parametrically estimated the average past-month prevalence of FMD. In doing so, we weighted BRFSS respondent records using composite weights created by multiplying pre-existing BRFSS design weights, making estimates population-representative, and age-standardization weights created by Klein and Schoenborn,[99] standardizing each study population in each year to the census-projected adult age distribution in 2000. We then calculated social inequities in FMD each year as the absolute difference in population FMD prevalences comparing referent and non-referent social groups under each social axis (e.g., those male and female respectively by interviewer-presumed sex).

3.2.4.2 Estimands of Interest and Estimation Approaches

As refundable State EITC policy availability varied throughout our study period (Appendix 3.C Figure 1), it was important that we accounted for compositional change over time in the set of states with and without refundable State EITC policies. Otherwise, we could not unbiasedly compare contemporaneous associations between State EITC policies and population mental distress over time, or attribute differences in trends in population mental distress to State EITC policies. While sample size constraints prohibited us from restricting our primary analysis to states always (N=5) or never (N=27) having a refundable State EITC during our study period, we: 1) excluded all states (N=5) which transitioned repeatedly between having and not having a refundable State EITC policy, 2) used the set of states which never offered a refundable State EITC policy during our study period as referent in all comparisons, and 3) repeated our overall comparisons in a sensitivity analysis restricting to the set of states always or never having a refundable State EITC.

3.2.4.2.1 State EITC Availability (Overall)

We compared annual FMD prevalences and social inequities in FMD across populations living in states with and without refundable State EITC policies in the prior tax. In doing so, we used the set of states that never had a refundable State EITC policy between 2000 and 2019 as referent.

3.2.4.2.2 State EITC Availability (Likely Eligible)

As our study specifically focuses on State EITC policies, we aimed to treat Federal EITC eligibility as a nuisance competing event and condition on it when examining the association between refundable State EITC availability and each of our outcomes among likely EITC-eligible individuals. While appropriately accounting for competing events is a common challenge in social policy research,[196] it is particularly difficult in our context as Federal and State EITCs typically target the same populations, share the same eligibility criteria, and are dispensed together. As the Federal EITC typically provides much larger credits to recipients,[182] it would also likely drive any observed association if not accounted for. Though our study is wholly descriptive and our associations are not intended to be interpreted causally, we used a non- traditional ‘differences-in-differences’ (DiD) estimator as described by Fougere and Jacquemet to isolate our association of interest.[197]

Traditional DiD estimators typically identify policy effects (associations) by comparing the difference in outcomes before and after a policy change for susceptible/eligible populations exposed and not exposed to that change.[198] The non-traditional estimator we use by contrast involves comparing the cross-sectional difference in outcomes between EITC-eligible and ineligible populations in states with and without available State EITC policies. As EITC-eligible individuals in both state groups would likely be eligible for a Federal EITC credit and EITC-ineligible individuals in both groups should not be affected by EITC policies absent misclassification or spillover effects, our comparison essentially 'subtracts out' any outcome difference related to Federal EITC eligibility assuming 1) Federal EITC eligibility is associated with our outcomes similarly in states with and without refundable State EITC policies and 2) non-refundable State EITC eligibility is not associated with our outcomes. We chose to use this non-traditional estimator over a traditional DiD estimator as these average exposure-outcome associations over time which we are interested in describing and can be biased when associations vary over time,[198] which we expect given refundable State EITC policies have changed generosity over time.

We define our estimator below, with Y our outcome, *FE* Federal EITC eligibility (1=Yes, 0=No), *SE* State EITC eligibility (1=Yes, 0=No), *SA* past-year State EITC availability (1=Yes, 0=No), and $\overline{SA}$ the history of State EITC availability (1= always available once implemented, 0=never available):

$$DiD = E\left[Y_{FE=1,SE=1} - Y_{FE=0,SE=0} \middle| SA = 1, \overline{SA} = 1\right] - E[Y_{FE=1} - Y_{FE=0} | SA = 0, \overline{SA} = 0] \quad (1)$$

As an interpretive example, if the annual DiD estimate for FMD prevalence were -2.0 percentage-points ('pp' hereafter) we would say that, among individuals likely eligible for an EITC, refundable State EITC availability was associated with a 2.0pp lower annual FMD prevalence.

3.2.4.2.3 Longitudinal Trend Summaries

To summarize longitudinal trends more succinctly, we calculated the weighted average annual change (AAC) in each outcome over time. We based this AAC on the set of annual estimates for each population deemed statistically reliable following National Center for Health Statistics (NCHS) guidelines (see Section 3.2.4.3), weighting each estimate-to-estimate change in annual outcomes based on the year interval between adjacent estimates. We define this AAC in (2), with Y our outcome of interest, *t* the year each estimate corresponds to, t_0 and T the year of our first and last unsuppressed estimates per group, *j* the year interval between adjacent unsuppressed estimates, ΔY_j the average annual change in Y over interval *j,* and J the total number of intervals for a given population:

$$AAC = \frac{\sum_{j=1}^{J} \Delta Y_j * j}{\sum_{j=1}^{J} j} = \frac{Y_T - Y_{t_0}}{T - t_0}, \text{ where } \Delta Y_j = \frac{Y_{t+j} - Y_t}{j} \quad (2)$$

To understand how longitudinal trends in each of our outcomes are associated with refundable State EITC availability, we applied the same difference and DiD approaches described in Section 3.2.4.1.3 using group-specific AAC estimates instead of cross-sectional outcomes. As another interpretive example, if the AAC DiD estimate for FMD prevalence were -0.1pp we would say that, among individuals likely eligible for an EITC, refundable State EITC availability was associated with a 0.1pp lower average annual change in FMD prevalence.

3.2.4.3 Data Suppression Approaches

To avoid presenting statistically unreliable findings we suppressed any annual FMD prevalence estimates or derived outcomes based in-part on those estimates (e.g., prevalence differences or DiD) if deemed statistically unreliable followed NCHS guidelines.[100] We outline these NCHS guidelines and discuss the extent of data suppression in Appendix 3.B.

3.2.4.4 Confidence Intervals

For each outcome we used a stratified bootstrapping approach based on intersectional social group membership to estimate percentile-based 95% Confidence Intervals (CI). This involved 1) resampling participants randomly with replacement many times (N=500) proportional to how common their joint race and ethnicity, sex, and household poverty status were each year, then 2) taking the 2.5th and 97.5th percentile estimates as lower and upper confidence limits.

All analyses were performed in R Version 4.0.3[101] using the RStudio IDE.[102]

3.3. Results

3.3.1 Study Population

BRFSS interviewed 7,826,425 non-institutionalized adults between 2000 and 2019, with 5,445,480 (70%) aged 18-64 years old, 4,621,683 (59%) meeting demographic eligibility criteria for inclusion in our study, and 3,872,989 (84% of this eligible subset) having sufficient information to be included in our study (Appendix 3.A). Demographically, our unweighted sample was primarily non-Hispanic white (78%), female (57%), and not living in household poverty (88%) (Table 3.1). Total annual samples ranged from 113,709 individuals in 2000 to 256,239 in 2011, with a median annual sample of 215,047 (Table 3.1).

Grouping states based on how consistently they had a refundable State EITC policy over our study period, 54% of individuals lived in states which never offered a refundable State EITC policy (our referent cohort), 37% lived in states which had a refundable State EITC in the prior tax-year (our primary analysis cohort), and 13% lived in states which always offered a refundable State EITC (our sensitivity analysis cohort) (Table 3.1). Across our sample, 22% of individuals were likely eligible for a Federal EITC and 19% were likely eligible for Federal and State EITCs when available. Compared to those living in states never having a refundable State EITC, those living in states with refundable policies were slightly more often male (43.5% vs. 42.2%) and Hispanic (8.2% vs. 6.9%) and less often non-Hispanic NAAN (1.3% vs. 2.4%) or in household poverty (11.5% vs. 12.8%), while those living in states always offering a State EITC were disproportionately non-Hispanic white (84.2% vs. 78.8%) and less often in household poverty (10.8% vs. 12.8%). Comparing those likely eligible to receive a State EITC credit to those not when available, EITC-eligible individuals were more often female (64.3% vs. 54.7%), non-Hispanic Black (16.3% vs. 7.4%, non-Hispanic NAAN (3.1% vs. 0.9%), Hispanic (19.9% vs. 5.6%), and living in household poverty (55.5% vs. 1.4%), and EITC eligibility group differences were similar restricting our comparison group to those in states always with a refundable State EITC policy (Table 3.1).

3.3.2 Comparing Overall Trends in FMD Prevalence Across EITC Contexts

The national age-standardized prevalence of FMD rose among working-aged adults from 10.4% in 2000 (95% CI: 10.2%, 10.8%) to 15.4% in 2019 (95% CI: 15.1%, 15.7%), reflecting an average year-over-year increase of 0.26pp (Table 3.2). While FMD prevalence rose across EITC contexts, this increase was more pronounced in states that never offered a refundable State EITC (AAC: +0.28pp) than in states that offered a refundable EITC in the prior tax year (AAC: +0.026pp, AAC PD: -0.02pp) or the subset of those states that always offered a refundable State EITC (AAC: +0.24pp, AAC PD: -0.03pp) (Figure 3.1, Table 3.3). Among individuals likely eligible for the EITC, access to a refundable State EITC in addition to the Federal EITC was associated with a 0.23pp lower average annual increase in FMD prevalence over time (AAC DiD: -0.23pp). This difference was likewise more pronounced when limiting our comparison to states that always offered a refundable State EITC (AAC DiD: -0.28pp).

As the availability and generosity of refundable State EITC policies changed repeatedly throughout our study period, we also examined whether the cross-sectional associations between State EITC availability and FMD prevalence changed over time. Between 2000 and 2019, past-year availability of a refundable State EITC was consistently associated with lower FMD prevalence and the magnitude of this association remained relatively stable over time (PD, 95% CI – 2000: -1.2pp, -2.0pp to -0.3pp. 2019: -1.8pp, -2.2pp to -0.8pp) (Appendix 3.C Figure 3, Table 3.3). This association was also larger in most years restricting our comparison to states that always offered a refundable State EITC. Among those likely eligible for the EITC, however, refundable State EITC availability has only been associated with lower FMD prevalence in recent years (DiD, 95% CI – 2000: +1.4pp, -1.8pp to +5.0pp. 2019: -2.8pp, -4.5pp to -1.1pp), though again with a greater point-estimated association when restricting to states always having refundable State EITCs (2019 DiD, 95% CI: -3.9pp, -6.2pp to -1.5pp).

3.3.2.2 Comparing Social Group-Specific Trends in FMD Prevalence Across EITC Contexts

National age-standardized FMD prevalence increased between 2000 and 2019 for all social groups defined by sex, race and ethnicity, and household poverty status (Table 3.2, Appendix 3.C Figure 2), with the smallest rate of increase for those Hispanic (AAC: +0.13pp) and largest for those non-Hispanic NAAN (AAC: +0.35pp). Comparing annual FMD prevalences across social groups, those living in household poverty consistently reported the highest annual FMD prevalence, followed closely by those non-Hispanic NAAN, while those non-Hispanic Asian consistently reported the lowest FMD prevalence (Table 3.2, Appendix 3.C Figure 2).

Refundable State EITC policy availability was associated with variable differences in FMD prevalence trends overall across social groups (Table 3.3). For those in poverty, female, and Hispanic, refundable State EITC availability was associated with smaller increases in FMD prevalence over time, while for those non-Hispanic Black, Asian, and NAAN they were associated with larger increases over time. Among those likely eligible to receive a State EITC, however, refundable State EITC availability was associated with smaller increases in FMD prevalence in all social groups except those in poverty, non-Hispanic NAAN and Black (Table 3.3).

Contemporaneous associations between past-year refundable State EITC availability and FMD prevalence also varied across social groups, though for most groups refundable State EITC availability was associated with lower point-estimated FMD prevalence throughout our study period (Table 3.3, Appendix 3.C Figure 3). Refundable State EITC availability was similarly associated with lower point-estimated FMD prevalence among those likely eligible to receive a State EITC, though less consistently over time and in most cases with 95% confidence intervals overlapping the null.

3.3.2.3 Comparing Trends in Social Inequities in FMD Across EITC Contexts

Social inequities changed variably throughout our study period at the national level (Table 3.2, Appendix 3.C Figure 2). Inequities narrowed somewhat for those non-Hispanic Black (vs. non-Hispanic white), remained steady for those female (vs. male), and widened for those in poverty (vs. not), non-Hispanic NAAN, non-Hispanic Asian, and Hispanic, with Hispanics and non-Hispanic Asians reporting lower FMD prevalence in 2019 than non-Hispanic whites (Table 3.2, Appendix 3.C Figure 2).

In interpreting the association between refundable State EITC availability and inequities, either contemporaneously or in terms of inequity trends, we need to consider the direction of differences in FMD prevalence between groups. Depending on whether those less privileged report lower or higher FMD prevalence, the same direction estimate can imply refundable State EITC availability is associated with a comparative narrowing or widening of inequities over time as we define them. For example, compared to those in states that never offered a refundable State EITC, past-year refundable State EITC availability was associated with an average annual difference in inequity trends of +0.08pp for those non-Hispanic NAAN and +0.09pp for those non-Hispanic Asian, using the difference in trends for those non-Hispanic white across EITC contexts as referent (Table 3.3). However, those non-Hispanic NAAN consistently reported higher FMD prevalence than non-Hispanic whites throughout our study period, while those non-Hispanic Asian consistently reported lower FMD prevalence (Appendix 3.C Figure 2). As such, the positive association between refundable State EITC availability and inequity trends implied a comparative widening of inequities over time for those non-Hispanic NAAN but a comparative narrowing of inequities for those non-Hispanic Asian as the prevalence difference between groups became closer to zero over time. We summarize our findings qualitatively for all social groups and EITC comparisons in Appendix 3.C Table 1.

Refundable State EITC availability was associated with narrowing sex-based inequities, poverty-based inequities, and race and ethnicity-based inequities for those non-Hispanic Asian but widening inequities for those non-Hispanic Black or NAAN (Table 3.3, Appendix 3.C Figure 3). Among those likely eligible for an EITC, refundable State EITC availability was associated with narrowing sex-based inequities but widening poverty- and race and ethnicity-based inequities.

Contemporaneously, past-year refundable State EITC was mostly associated with smaller point-estimated annual social inequities in FMD for those female, in poverty, and non-Hispanic Asian, but larger social inequities those non-Hispanic Black and Hispanic. Past-year refundable State EITC availability was not consistently associated with differences in annual social inequities in FMD for any social group when restricting to those likely eligible to receive an EITC, in-part due to 95% confidence intervals overlapping the null across comparisons.

3.4. Discussion

To our knowledge, our study is the first to assess how, if at all, refundable State EITC policies are associated with longitudinal trends in FMD prevalence and social inequities in FMD. Summarizing our results, we found that refundable State EITC availability was associated with smaller increases in FMD prevalence over time and lower contemporaneous FMD prevalence throughout our study period; particularly among those likely eligible to receive a State EITC, and in states where refundable State EITC policies were available for longer. Refundable State EITC availability was also associated with smaller increases in FMD prevalence over time for those in poverty, female, and Hispanic as well as narrowing sex- and poverty-based social inequities in FMD over time. At the same time, State EITC availability was associated with greater increases in FMD prevalence over time for most racially minoritized groups, widening race and ethnicity-based inequities for those non-Hispanic Black and NAAN, and rising FMD prevalence among individuals in poverty likely eligible for an EITC.

While investigating counter-intuitive findings is beyond the scope of our analysis, there are several artefactual and substantive explanations for our findings. First, there are likely individual- and state-level differences between EITC groups that would be considered confounding variables in a causal context. For example, states with State EITC policies tend to have more highly educated populations[199] and educational attainment is a strong determinant of mental distress.[170] Likewise, states with and without State EITC policies are unevenly distributed across the US, with Northeast and Midwestern states more likely to adopt State EITC policies and Southern states less likely. This could partly explain why State EITC availability is associated with worse mental health for Black individuals overall, as Black Americans in the Northeast and Midwest have historically reported worse mental distress than those in the South.[200] Population compositional change could also help explain our finding that State EITC availability was associated with larger increases in FMD prevalence among those in poverty likely eligible for a State EITC. For example, if a greater share of those in poverty in 2019 (vs. 2000) in states with (vs. without) State EITC policies were from groups with historically higher FMD prevalence (e.g., women or those non-Hispanic NAAN), this could explain our counter-intuitive result. Differential take-up of the EITC by race and poverty status could also help explain why the association between State EITC availability and FMD prevalence is heterogeneous across social groups. While those in poverty and non-Hispanic NAAN are more likely to be eligible for EITCs [201,202] they are less likely to receive them,[203] such as due to not filing a tax return.[204] Finally, it is also possible that State EITCs worsen recipient mental health; particularly among those in poverty. This could be because they make individuals more aware of their financial precarity without offering a means to address it[180] or because EITC work requirements induce individuals into low-quality employment, which can be as if not more harmful to mental health than unemployment.[205,206]

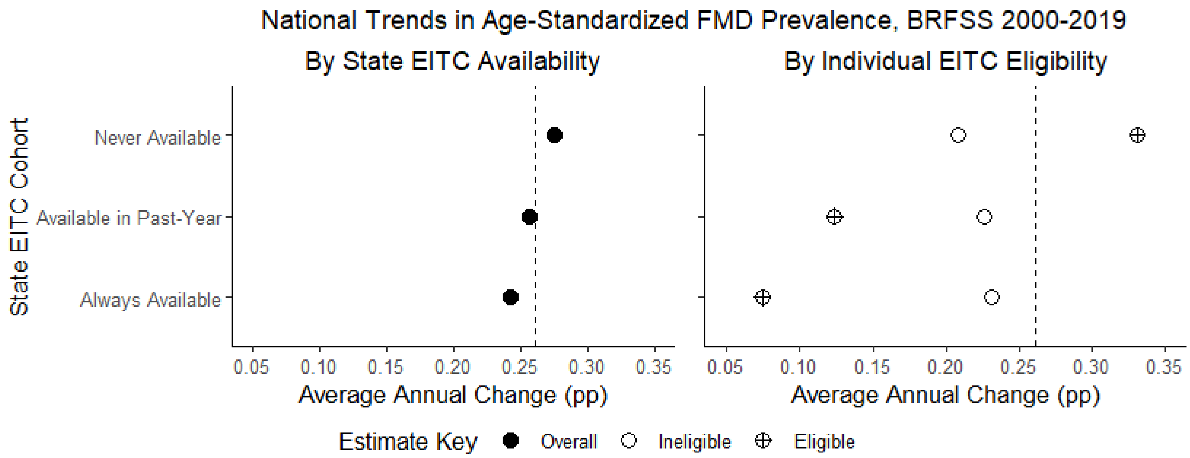
Reviewing the literature, we identified nine studies examining the relationship between State EITC policies and mental health.[172,182–187,207,208] These studies are somewhat difficult to compare, however, given they consider different study populations, analytic periods, and State EITC exposures (e.g., past-year availability versus eligibility). Five studies examined the association between refundable State EITC availability and mental health,[183–187] with four finding State EITC availability was associated with improved mental health among those most-likely eligible for credits (i.e., less educated adults and/or women with dependent children). Though we reached similar overall conclusions to this literature, our findings suggest this association does not hold for all social groups and has likely varied over time. Separately, four studies examined the association between State EITC eligibility and mental health, reaching mixed conclusions.[172,182,207,208] Shields-Zeeman *et al.* and Schmidt *et al.* found past-year State EITC eligibility was associated with reduced psychological distress,[172,208] while Collin *et al.* and Jones *et al.* found no association considering past-year and lifetime EITC credit amount eligibility respectively.[182,207] Of note, only Collin *et al.*[182] separated State EITC credits from other tax credits like the Federal EITC or Child Tax Credit (CTC) and so can be interpreted as the impact of State EITC policies alone. Our study adds to this literature in that we find past-year State EITC availability has consistently been associated with lower point-estimated FMD prevalence among EITC-eligible individuals throughout our study period, though with important heterogeneity across social groups.

In interpreting our findings, several limitations should be noted. First, we expect non-differential misclassification in our determination of likely State EITC eligibility, biasing the association between State EITC eligibility and FMD prevalence towards the null. By necessity, our determination relied on imputed household incomes which could not be tested in terms of their accuracy or differentiate between those with no earned income, who are ineligible for EITCs, or with low income. Second, our average annual trend estimates and comparisons must be interpreted with caution for various reasons. BRFSS changed its survey methodology in 2011 to minimize selection bias, limiting the comparability of estimates pre- and post-2011; trends may be non-linear, which our linear measure could summarize poorly; trends for some groups rely on a reduced set of annual estimates, limiting their comparability with other group trends; and our AAC as calculated only relies on each group's first and last annual estimate, which could result in poor trend summaries if either annual estimate were an outlier. While we do not observe any discontinuities in annual outcomes pre- and post-2011, most group trends appear linear, few group trends were based on a markedly reduced set of estimates, and no tail-end estimates were clear outliers, these should still be considered by readers. Third, we expect some bias related to state and population compositional change in our associations between State EITC availability and outcome trends over time. While our sensitivity analysis compared the same set of states over time and reached similar conclusions to our primary analysis, we do not account for demographic compositional change which could contribute towards our observed trends. Additional limitations include our restriction to complete cases and BRFSS exclusion of incarcerated adults and those experiencing homelessness, which would both be expected to under-count FMD prevalence among socially disadvantaged groups, and our use of a self-reported mental health measure which does not directly map to diagnostic conditions like depression, limiting the comparability of our study to other literature.

In summary, our findings suggest that State EITC policies are an important fiscal tool for improving population mental health (or equally, slowing its decline) but raise questions over whether these policies – in their current form – are effective tools for improving mental health equity. As such, in the ongoing push to expand State EITC policies nationwide,[209] equity-oriented policymakers should seek to identify how these policies can be adapted to improve mental health equity more effectively, such as through increasing EITC uptake, broadening program eligibility, or improving their absolute generosity.[210–212]

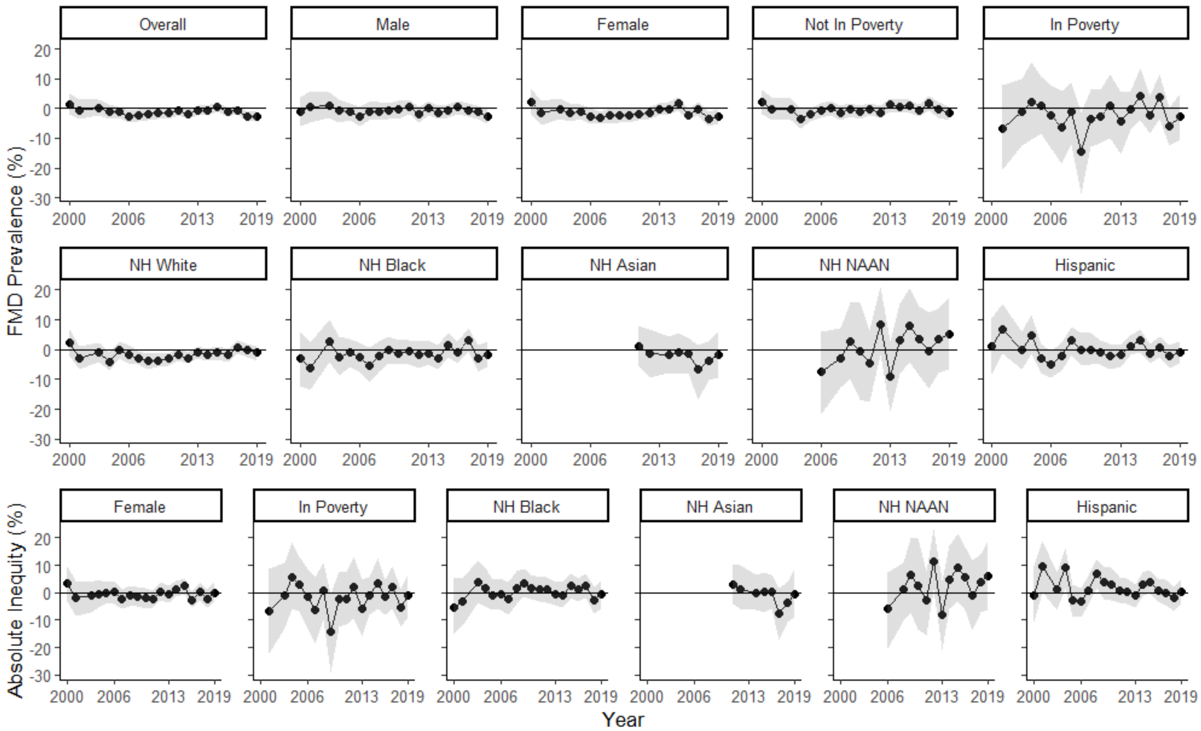
3.5. Relevant Tables and Figures

Figure 3.1. Trends in Age-Standardized FMD Prevalence, BRFSS 2000-2019.



Legend. EITC: Earned Income Tax Credit. FMD: Frequent Mental Distress. pp: percentage-point. Note: In states with refundable State EITC policies, 'ineligible' refers to those not eligible for either Federal or State EITCs while 'eligible' refers to those eligible for Federal and State EITCs. Those eligible for one policy and ineligible for another are excluded.

Figure 3.2. Association Between State EITC Availability, FMD Prevalence, and Social Inequities Over Time Among Those Likely Eligible for a State EITC, BRFSS 2000-2019.



Legend. EITC: Earned Income Tax Credit. FMD: Frequent Mental Distress. NH: Non-Hispanic. NAAN: Native American or Alaska Native. Note: Note: All estimates are DiD estimates comparing the differences in FMD prevalences or absolute inequities for same populations eligible (vs. ineligible) for EITC policies in longitudinal state cohorts with a refundable State EITC in the prior tax year versus never having a refundable State EITC throughout our study period. In states with refundable State EITC policies, 'ineligible' refers to those not eligible for either Federal or State EITCs while 'eligible' refers to those eligible for Federal and State EITCs. Those eligible for one policy and ineligible for another are excluded. Those male, non-Hispanic white, and not living in household poverty are used as referent for sex-, race and ethnicity-, and poverty-based inequities respectively.

Table 3.1. Unweighted Demographic Characteristics of Study Population, BRFSS 2000-2019.

Population Characteristic – N (%)		**Overall**	**State EITC Available**			**State EITC Eligibility**			
			No (Never) **Both**	Yes (Past-Year) **Primary**	Yes (Always) **Sensitivity**	No (Past-Year) **Primary**	Yes (Past-Year) **Primary**	No (Always) **Sensitivity**	Yes (Always) **Sensitivity**
	Total	3.872,989	2,086,403 (53.9)	1,423,775 (36.8)	504,787 (13.0)	1,157,532 (81.3)	266,243 (18.7)	419,317 (83.1)	85,470 (16.9)
	Median Annual	215,047	112,109	86,863	26,899	69,360	17,230	22,407	4492
Presumed Sex	Male	1,651,521 (42.6)	881,315 (42.2)	619,892 (43.5)	221,326 (43.8)	524,742 (45.3)	95,150 (35.7)	190,869 (45.5)	30,457 (35.6)
	Female	2,221,468 (57.4)	1,205,088 (57.8)	803,883 (56.5)	283,461 (56.2)	632,789 (54.7)	171,094 (64.3)	228,447 (54.5)	55,014 (64.4)
Self-Identified Race and Ethnicity	NH White	3,035,354 (78.4)	1,643,774 (78.8)	1,127,138 (79.2)	425,138 (84.2)	970,502 (83.8)	156,636 (58.8)	370,034 (88.2)	55,104 (64.5)
	NH Black	355,680 (9.2)	198,149 (9.5)	129,244 (9.1)	29,419 (5.8)	85,969 (7.4)	43,275 (16.3)	19,203 (4.6)	10,216 (12.0)
	NH Asian	94,110 (2.4)	51,643 (2.5)	31,211 (2.2)	11,618 (2.3)	26,036 (2.2)	5175 (1.9)	9349 (2.2)	2269 (2.7)
	NH NAAN	72,669 (0.9)	49,259 (2.4)	18,868 (1.3)	5266 (1.0)	10,643 (0.9)	8225 (3.1)	3308 (0.8)	1958 (2.3)
	Hispanic	315,176 (8.1)	143,567 (6.9)	117,314 (8.2)	33,346 (6.6)	64,382 (5.6)	52,932 (19.9)	17,424 (4.2)	15,922 (18.6)
Household Poverty Status	Not In Poverty	3,394,310 (87.6)	1,819,277 (87.2)	1,259,641 (88.5)	450,479 (89.2)	1,141,209 (98.6)	118,432 (44.5)	412,329 (98.3)	38,150 (44.6)
	In Poverty	478,679 (12.4)	267,126 (12.8)	164,134 (11.5)	54,308 (10.8)	16,323 (1.4)	147,881 (55.5)	6987 (1.7)	47,321 (55.4)

EITC: Earned Income Tax Credit. NH: Non-Hispanic. NAAN: Native American or Alaska Native. Percentages are row-wise for 'Total' and column-wise for all other population summaries. Note: Parentheses next to 'No' and 'Yes' denote longitudinal State EITC availability cohort. Boldened 'both', 'primary' and 'sensitivity' refer to the analyses each cohort population contributes towards. We do not present summaries for populations in states which would implement a refundable State EITC prior to their implementation. State EITC eligible populations only include those living in states with refundable State EITC policies in the prior tax-year.

Table 3.2. Trends in National FMD Prevalence and Social Inequities, BRFSS 2000-2019.

Population Characteristics		FMD Prevalence (%)			Absolute Inequity (PD, %)		
		AAC	2000 (95% CI)	2019 (95% CI)	AAC	2000 (95% CI)	2019 (95% CI)
	Overall	+0.26	10.4 (10.2, 10.8)	15.4 (15.1, 15.7)	-	-	-
Presumed Sex	Male	+0.26	7.8 (7.3, 8.2)	12.8 (12.4, 13.2)	-	Ref	Ref
	Female	+0.26	13.2 (12.7, 13.6)	18.0 (17.5, 18.6)	-0.01	+5.4 (+4.7, +6.1)	+5.2 (+4.6, +5.9)
Self-Identified Race and Ethnicity	NH White	+0.32	10.3 (10.0, 10.6)	16.4 (16.0, 16.8)	-	Ref	Ref
	NH Black	+0.24	11.6 (10.6, 12.5)	16.2 (15.2, 17.3)	-0.08	+1.3 (+0.3, +2.3)	-0.2 (-1.3, +0.9)
	NH Asian	+0.15	7.9 (5.4, 11.3)	10.7 (9.1, 12.3)	-0.17	-2.4 (-5.1, +1.1)	-5.7 (-7.4, -4.0)
	NH NAAN	+0.35	15.3 (11.9, 19.0)	22.0 (19.1, 25.0)	+0.03	+5.0 (+1.5, +8.7)	+5.6 (+2.6, +8.6)
	Hispanic	+0.13	10.7 (9.6, 11.9)	13.3 (12.4, 14.3)	-0.19	+0.5 (-0.7, +1.7)	-3.1 (-4.1, -2.1)
Household Poverty Status	Not In Poverty	+0.22	9.5 (9.2, 9.8)	13.6 (13.3, 14.0)	-	Ref	Ref
	Poverty	+0.26	17.6 (16.2, 19.1)	22.5 (21.6, 23.3)	+0.04	+8.0 (+6.6, +9.6)	+8.9 (+7.9, +9.8)

FMD: Frequent Mental Distress. NH: Non-Hispanic. PD: Prevalence Difference. AAC: Average Annual Change in percentage-points. CI: Confidence Interval.

Table 3.3. Association Between Refundable State EITC Availability, FMD Prevalence and Social Inequities, BRFSS 2000-2019.

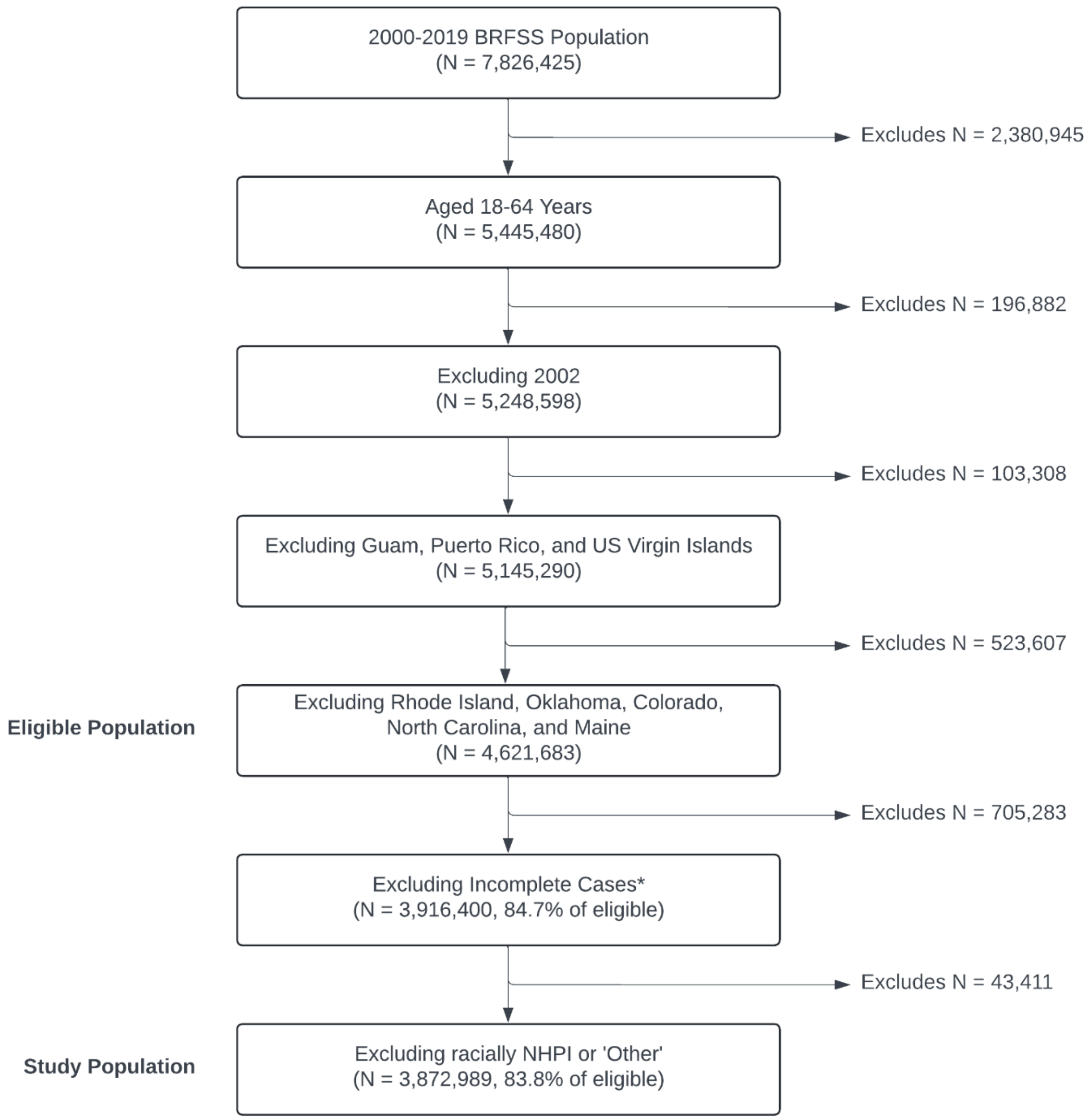
Table 3: Association Between Refundable State EITC Availability, FMD Prevalence and Social Inequities, BRFSS 2000 – 2019.

Population Characteristics		Association Between State EITC Availability and Each Outcome									
		Across our Whole Sample (PD)					Among those EITC-Eligible (DiD)				
		Year Range	FMD Prevalence (%)		Absolute Inequity (PD, %)		Year Range	FMD Prevalence (%)		Absolute Inequity (PD, %)	
			AAC	2019 (95% CI)	AAC	2019 (95% CI)		AAC	2019 (95% CI)	AAC	2019 (95% CI)
Overall (Primary)		2000 – 2019	-0.02	-1.5 (-2.2, -0.8)	-	-	2000 – 2019	-0.23	-2.8 (-4.5, -1.1)	-	-
Overall (Sensitivity)		2000 – 2019	-0.03	-1.8 (-2.7, -0.8)	-	-	2000 – 2009	-0.28	-3.9 (-6.2, -1.5)	-	-
Presumed Sex	Male	2000 – 2019	+0.00	-1.0 (-1.9, -0.1)	Ref	Ref	2000 – 2019	-0.08	-2.7 (-5.2, -0.2)	Ref	Ref
	Female	2000 – 2019	-0.04	-2.0 (-3.1, -1.1)	-0.04	-1.0 (-2.4, +0.2)	2000 – 2019	-0.26	-2.7 (-5.0, -0.3)	-0.18	+0.1 (-3.2, +3.7)
Self-Identified Race and Ethnicity	NH White	2000 – 2019	+0.00	-1.4 (-2.2, -0.7)	Ref	Ref	2000 – 2019	-0.17	-1.1 (-3.6, +1.2)	Ref	Ref
	NH Black	2000 – 2019	+0.06	+0.3 (-1.8, +2.3)	+0.06	+1.7 (-0.4, +3.9)	2000 – 2019	+0.08	-1.5 (-5.8, +2.5)	+0.25	-0.4 (-6.0, +4.5)
	NH Asian	2000 – 2019	+0.09	+2.3 (-0.7, +5.1)	+0.09	+3.7 (+0.4, +6.7)	2011 – 2019	-0.32	-1.6 (-9.5, +6.5)	-0.42	-0.5 (-8.9, +8.6)
	NH NAAN	2001 – 2019	+0.30	+3.4 (-2.7, +9.2)	+0.34	+4.8 (-1.2, +11.0)	2006 – 2019	+0.98	+5.1 (-6.4, +17.9)	+0.93	+6.3 (-6.1, +19.0)
	Hispanic	2000 – 2019	-0.11	-2.1 (-4.0, -0.4)	-0.11	-0.7 (-2.6, +1.1)	2000 – 2019	-0.09	-0.8 (-4.5, +2.9)	+0.08	+0.3 (-4.2, +4.9)
Household: In Poverty	No	2000 – 2019	+0.01	-1.0 (-1.7, -0.2)	Ref	Ref	2000 – 2019	-0.19	-1.7 (-4.1, +0.7)	Ref	Ref
	Yes	2000 – 2019	-0.28	-5.0 (-6.8, -3.1)	-0.29	-4.0 (-6.1, -1.9)	2001 – 2019	+0.24	-2.6 (-10.3, +5.0)	+0.33	-0.9 (-9.0, +7.0)

EITC: Earned Income Tax Credit. FMD: Frequent Mental Distress. NH: Non-Hispanic. DiD: Difference-in-Difference. PD: Prevalence Difference. AAC: Average Annual Change in percentage-points. CI: Confidence Interval. Note: As non-Hispanic Asians reported lower age-standardized FMD prevalence than non-Hispanic whites throughout follow-up, negative DiD estimates for this group indicate State EITC availability is associated with comparatively wider/widening social inequities.

3.6. Relevant Appendices.

Appendix 3.A. Figure 1. Study Inclusion Flow Diagram, BRFSS 2000-2019.



Legend. BRFSS: Behavioral Risk Factor Surveillance System. NHPI: Native Hawaiian or Pacific Islander. * Incomplete cases refer to respondents with missing sex, ethnicity, race (if known non-Hispanic), marital status, state of residence, number of adults and children in household, categorized household income, or reported number of past-month mentally unhealthy days.

Appendix 3.B. Summarizing NCHS data suppression of year-specific FMD prevalence, social inequities, and State EITC-based difference estimates overall and for each social axis between 2000 and 2019, BRFSS 2000-2019.

Describing NCHS Data Suppression Guidelines

Current NCHS guidelines recommend masking proportion estimates where: 1) the effective sample size n_e contributing to an estimate accounting for design effects is less than 30, with

$$n_e = \frac{Sample\ Size}{Design\ Effect} = \frac{n}{\frac{\widehat{var}(\hat{p})}{\hat{p}(1-\hat{p})/n}} = \frac{\hat{p}(1-\hat{p})}{\widehat{var}(\hat{p})},$$

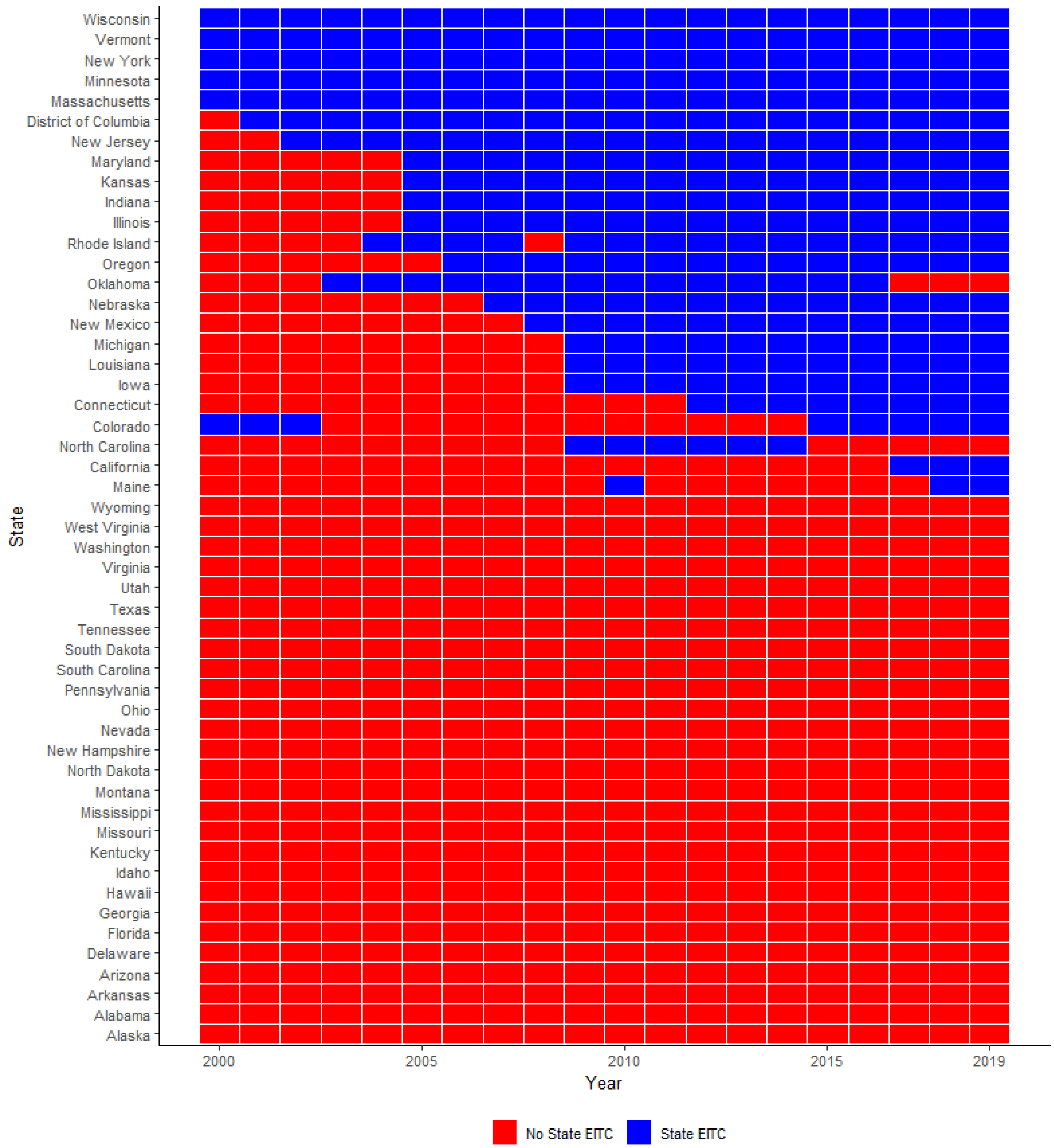
where $\hat{p}$ is the point-estimated FMD prevalence as a proportion; 2) either no-one or everyone in a population reports FMD (i.e., $\hat{p}$ equals 0 or 1); 3) the absolute width of an estimate's 95% confidence interval (CI) is more than 30% (i.e., upper 95% CI– lower 95% CI > 0.3); or 4) the absolute width of an estimate's 95% CI is more than 130% the size of the estimate itself (i.e., absolute 95% CI width divided by $\hat{p}$ is >1.3).[100]

The Extent of Data Suppression following NCHS Suppression Guidelines

Following NCHS guidelines, zero annual FMD prevalence estimates were suppressed for the total population or for populations defined individually by sex, poverty status, or race and ethnicity overall. When jointly stratifying by past-year refundable State EITC availability and likely eligibility across primary analysis longitudinal State EITC availability cohorts, zero estimates were suppressed for those male, female, non-Hispanic white, non-Hispanic Black, Hispanic, or not in poverty. Likewise, only one strata-specific annual estimate (of 76, 1.3%) was suppressed for those in poverty. Estimate suppression was somewhat higher for those non-Hispanic NAAN (N=10 of 76, 13.2%) or non-Hispanic Asian (N=18 of 76, 23.7%). Estimate suppression was likewise higher across sensitivity analysis longitudinal State EITC availability cohorts, with 10 annual estimates suppressed for those in poverty (13.2%), 23 for those non-Hispanic NAAN (30.3%), and 32 for those non-Hispanic Asian (42.1%).

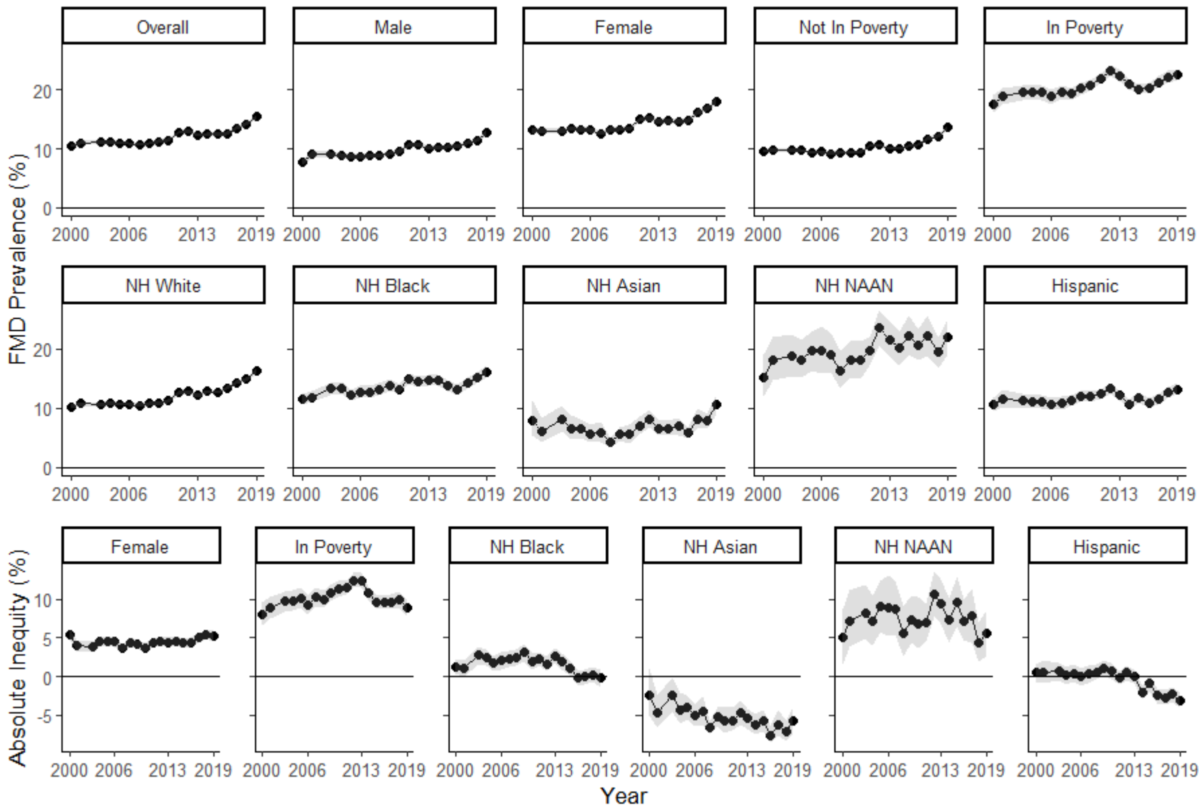
Appendix 3.C. Additional Study Figures and Tables.

Appendix 3.C. Figure 1. Past-Year Refundable State EITC Policy Availability, UKCPR 2000-2019.



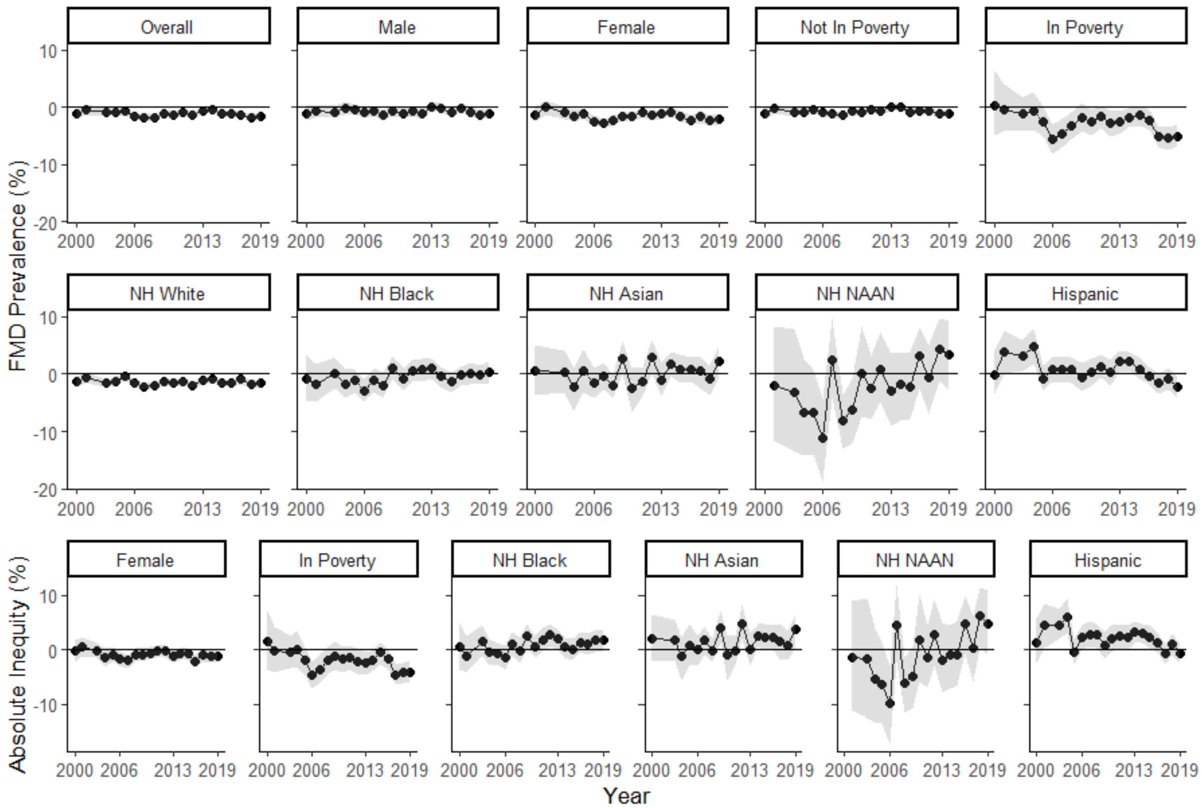
Legend. EITC: Earned Income Tax Credit. UKCPR: University of Kentucky Center for Poverty Research National Welfare Database. Note: States with non-refundable State EITC policies are categorized as 'No'.

Appendix 3.C. Figure 2. National Trends in FMD Prevalence and Social Inequities Over Time, BRFSS 2000-2019.



Legend. EITC: Earned Income Tax Credit. FMD: Frequent Mental Distress. PD: Prevalence Difference. NH: Non-Hispanic. NAAN: Native American or Alaska Native. Note: Those male, non-Hispanic white, and not living in household poverty are used as referent for sex-, race and ethnicity-, and poverty-based inequities respectively.

Appendix 3.C. Figure 3. Annual Association Between State EITC Availability, FMD Prevalence and Social Inequities Over Time, BRFSS 2000-2019.



Legend. EITC: Earned Income Tax Credit. FMD: Frequent Mental Distress. NH: Non-Hispanic. NAAN: Native American or Alaska Native. Note: All estimates are prevalence difference comparing the same population in longitudinal state cohorts with a refundable State EITC in the prior tax year versus never having a refundable State EITC throughout our study period. Those male, non-Hispanic white, and not living in household poverty are used as referent for sex-, race and ethnicity-, and poverty-based inequities respectively.

Appendix 3.C. Table 1. Qualitatively Summarizing Associations Between State EITC Availability and Eligibility with FMD Prevalence and Social Inequity Trends, BRFSS 2000-2019.

Refundable State EITC Exposure	Population		Trend Association: FMD Prevalence	Trend Association: Absolute Inequity	2019 Association: FMD Prevalence	2019 Association: Absolute Inequity
Availability (Yes vs. No)	Overall	Primary	Lower	-	Lower *	-
		Sensitivity	Lower	-	Lower *	-
	Presumed Sex	Male	None	-	Lower *	-
		Female	Lower	Narrowing	Lower *	Smaller
	Self-Identified Race and Ethnicity	NH White	None	-	Lower *	-
		NH Black	Higher	Widening	None	Larger
		NH Asian	Higher	Narrowing	Higher	Smaller *
		NH NAAN	Higher	Widening	None	Larger
		Hispanic	Lower	Mixed	Lower *	None
	Household Poverty Status	Not In Poverty	None	-	Lower *	-
		In Poverty	Lower	Narrowing	Lower *	Larger *
Eligibility (Yes vs. No)	Overall	Primary	Lower	-	Lower *	-
		Sensitivity	Lower	-	Lower *	-
	Presumed Sex	Male	Lower	-	Lower *	-
		Female	Lower	Narrowing	Lower *	None
	Self-Identified Race and Ethnicity	NH White	Lower	-	Lower	-
		NH Black	Higher	Widening	None	None
		NH Asian	Lower	Widening	None	None
		NH NAAN	Higher	Widening	Higher	Larger
		Hispanic	Lower	Narrowing	None	None
	Household Poverty Status	Not In Poverty	Lower	-	Lower	-
		In Poverty	Higher	Widening	Lower	None

FMD: Frequent Mental Distress. EITC: Earned Income Tax Credit. NH: Non-Hispanic. NAAN: Native American or Alaska Native. Note: We describe the direction of association of trends for each outcome over time. Cells are shaded red where trend associations either indicates faster-increasing FMD prevalence over time or changes to inequities favoring those conceptually most-privileged. Cells marked '*' do not have 95% CI overlapping the null. Cells are shaded green where trend associations either indicates slower-increasing FMD prevalence over time or changes to inequities favoring those conceptually less-privileged. Cell shading qualitatively incorporates the point-estimate as well as the 95% CI width, and so very unreliable estimates with large point-estimates may be marked 'none'.

Chapter 4.

How Can We Adapt Earned Income Tax Credit Policies to Promote Economic and Mental Health Equity? Simulating the Impacts of Five Federal and State EITC Policy Reforms.

How Can We Adapt Earned Income Tax Credit Policies to Promote Economic and Mental Health Equity? Simulating the Impacts of Five Federal and State EITC Policy Reforms.

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Abstract:

Earned Income Tax Credit (EITC) policies are some of the largest means-tested cash transfer programs in the US, providing income support to over 26 million Americans in 2019. However, there are several ways in which these policies fall short of their potential to reduce poverty and improve social equity. Using respondent information from the 2019 Behavioral Risk Factor Surveillance System (BRFSS), we simulated the potential impacts of five Federal and State EITC policy reforms on EITC expenditures, numbers of likely EITC recipients, typical credit eligibilities, numbers lifted out of poverty, and population mental distress compared to existing policy in 2019. We find that increasing the generosity of the EITC, expanding the “childless” EITC, eliminating the EITC phase-in structure, and expanding State EITC availability and refundability would all substantially reduce poverty and improve economic wellbeing. However, we also find that expanding the “childless” EITC and extending the credit plateau for married filers would likely widen social inequities in income and poverty, and that none of the EITC reforms we assessed would likely reduce population mental distress. As policymakers increasingly look to advance social equity through tax and social assistance policy, our findings raise important implications for how to do so effectively.

4.1. Introduction

4.1.1 Background

Over recent decades government tax and transfer policies like the Earned Income Tax Credit (EITC) have played an increasingly important role in preventing poverty,[213] constraining rising income inequality,[214] and improving racial equity.[209] Because economic resources are important determinants of health and health equity,[57,171,215,216] these policies also play a significant role in shaping population mental health and mitigating growing social disparities in mental distress.[38,170,185,186] Despite these benefits, however, income inequality and mental health equity continue to worsen across the US.[170,214] In this context, it is important that policymakers understand how EITC policies could be reformed to mitigate these trends more effectively.

EITC policies are some of the largest government transfer programs targeting low-to-moderate income workers in the US.[36] In addition to the Federal EITC, they have been implemented in 31 states, the District of Columbia (DC) and Puerto Rico, and collectively provided $57 billion to 23 million workers in 2023. Because of social inequities in earnings,[217] the EITC disproportionately benefits low-income women, racially minoritized groups, and those with less education.[37] In addition, because EITCs are means-tested, they are typically one of the most progressive tax expenditures in federal and state tax codes[218] and serve an important purpose offsetting income and payroll taxes for low-income workers. EITCs are typically refundable tax credits, meaning that claimants receive a cash refund if the EITC they are entitled to is greater than their total taxes owed. They follow a three-part structure intended to incentivize work with credit size rising alongside initial labor earnings (the ‘phase-in’ period), plateauing, and then falling again as adjusted gross income increases further (the ‘phase-out’ period) (Figure 4.1A). EITC credit size also varies based on marital status and number of dependent children, with credit sizes increasing with number of dependents and the EITC phasing out later for those married. While state policies vary in their eligibility criteria and generosity, most follow the same structure as the Federal EITC and match their generosity to some percentage of the equivalent Federal EITC claimants are eligible for (e.g., Connecticut matched 40% of the Federal EITC in 2023, meaning that a filer eligible for a $100 Federal EITC would also be eligible for a $40 State EITC in Connecticut).

While EITC policies effectively alleviate poverty[37,213] and appear to protect the mental health of recipients,[172,208,219] there are several ways in which these policies fall short of their potential to improve social equity and uplift underserved communities. These broadly concern restrictive eligibility criteria, low generosity, and the unavailability and non-refundability of State EITC policies across the US. The purpose of our study was to simulate how five Federal and State EITC policy reforms defined in Section 4.2.2.2.2 would impact national EITC expenditures, EITC recipiency rates, average credit sizes, numbers lifted out of poverty, and population prevalences of frequent mental distress (FMD) had they been implemented in 2019. In doing so we examined how each policy would differently benefit social groups defined by race, ethnicity, sex, educational attainment, and household poverty status, with and without restricting to likely current EITC recipients under existing policy.

4.2. Methods

4.2.1 Study Design and Data

We conducted a simulation study using respondent information from the 2019 Behavioral Risk Factor Surveillance System (BRFSS) and EITC policy information from the University of Kentucky Center for Poverty Research (UKCPR) National Welfare Database.[220] The BRFSS is a set of state-administered telephone surveys interviewing over 400,000 non-institutionalized adults each year across the 50 states, District of Columbia (DC), Guam, Puerto Rico, and US Virgin Islands. It collects extensive sociodemographic and health information on participating individuals and their households and can be made representative at state and national levels through sample weighting.[87,88] The UKCPR National Welfare Database meanwhile collects information on past-year EITC policy characteristics for all 50 states and DC, which we supplement with additional policy information extracted from federal and state tax codes and the National Bureau for Economic Research (NBER) TAXSIM 35 tax simulator model.[190] Based on individual state residences, ages, family characteristics and imputed household incomes, we simulated the expected Federal and State EITC credit individuals would likely be entitled to under existing policy as well as each of our proposed policy changes. We then modelled the relationship between likely credit eligibility and individual mental distress under existing policy and used this model to simulate how each of our proposed policy changes would have affected population mental distress in 2019, had they been implemented.

We restricted our analysis to adults 18 to 64 years old, residing in the 50 states and DC, and identifying as white, Black, Asian, or Native American or Alaska Native (NAAN) and with complete information on all respondent-level study variables: participant age, presumed sex, self-identified race and ethnicity, highest educational attainment, household income, marital status, number of dependents, employment status, home ownership status, residence rurality, and self-reported mental health.

4.2.2 Measures

4.2.2.1 Outcomes

We examined the potential impacts of our proposed policy reforms on three outcomes: 1) EITC expenditures; 2) population summaries of individual EITC receipt, credit size, and changes in poverty status; and 3) population prevalences of frequent mental distress (FMD) as below:

EITC Expenditures: We calculated expected total, Federal and State EITC expenditures by taking the population-weighted sum of all relevant individual credits. To account for the fact that not all eligible claimants receive an EITC, we then adjusted these expenditures based on the state-specific EITC participation rates estimated by the Internal Revenue Service (IRS) for 2019.[221]

Individual EITC receipt, credit size, and change in poverty status: For each policy scenario, we categorized individuals as likely recipients or non-recipients of Federal and/or State EITC credits, recorded the Federal and State EITC credits they or their household would likely be entitled to, and determined whether the combined Federal and State EITC they would be entitled to would lift their imputed household income (see Section 4.2.2.3) above the state-adjusted Official Poverty Measure (OPM) threshold for their household size, number of dependents, and state of residence (see Section 4.2.2.3) if originally below this threshold. We then created population-weighted summaries of each measure as presented in Table 4.3, assuming full EITC uptake.

FMD Prevalence: As part of the core BRFSS questionnaire administered in all states, participants are asked the CDC 'health-related quality of life' (HRQOL) question "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?".[89] Participants can respond 0 to 30, with those responding ≥14 days categorized as experiencing frequent mental distress (FMD). This measure as well as its dichotomization have been in-use since 1993 and shown to have good internal validity and test-retest reliability across common study populations.[89,90] Using our fitted model (see Section 4.2.3.3), we then predicted the probability of each individual experiencing FMD under each policy scenario assuming full EITC uptake and used these in estimating population-weighted annual prevalences of past-month FMD.

4.2.2.2 Exposures

A key goal of our study was to identify the relative winners and losers of different EITC policy reforms and to understand their wider impacts on social economic and mental health equity. To enrich this comparison, we chose policy reforms targeting different income groups and family compositions, occurring at state and federal levels, and necessitating different types of policy change that may be more or less politically feasible. For example, while federal changes would have the largest aggregate effect if implemented (e.g., through benefiting a larger population and affecting State EITC policies that follow the federal schedule), increasing political polarization has made the US Congress less productive[222] and state legislatures increasingly important in shaping health and welfare policy.[223,224] Likewise, while there is more bipartisan support for expanding the "childless" EITC,[225] eliminating work requirements in the EITC or its phase-in structure would require larger and more controversial structural change.[226] The policy proposals we consider are defined below and visually presented in Figure 4.1. The issues each proposal aims to address are summarized in Table 4.1. State-specific details on the operationalization of each proposal are also provided in Appendix 4.A.

Policy 1: Extending refundable State EITC policies nationwide, with all states currently not implementing a policy or implementing a non-refundable policy instead offering a refundable State EITC equivalent to the median credit offered to similar individuals (i.e. those with the same income, marital status, and number of dependents) in states with refundable policies in 2019 (Figure 4.1B). Under this proposal, 21 states would newly adopt a State EITC policy and five states would have their non-refundable policy replaced with a refundable policy, matching 15-17% of the Federal EITC depending on family size.

Policy 2: Increasing the generosity of the Federal EITC by 10% for all filers (Figure 4.1C). Where State EITC policies matched some percentage of the Federal EITC in 2019, this reform would also increase those State EITC generosities by 10%. As modelled, this would affect all State EITC policies except those in California, which follows a markedly different structure, and Minnesota, which, while mirroring the Federal EITC structure, follows its own schedule.

Policy 3: Making the EITC available to all workers aged 18 or older without dependents (including those in full-time education) and adopting the banding structure in place under the 2021 American Rescue Plan Act (ARPA) for “childless” workers (Figure 4.1D). Under existing policy in 2019, workers without dependents could only claim an EITC if aged 25 to 64 years old. Meanwhile, under ARPA workers 19 years or older without dependents could claim an EITC if they were not students. Our proposal extends EITC benefits to all those under 25 without dependents regardless of their educational status, recognizing that most students support themselves financially throughout college,[227] that financial precarity is one 0-of the leading causes of students to drop out of college,[228] and that both of these points are especially true for low-income and racially minoritized students. Our proposal also extends these structural changes to all State EITC policies except those in California, Minnesota, and Wisconsin, which did not offer an EITC for those without dependents. Smaller state-specific distinctions are also relevant for Indiana, Iowa, and DC (see Appendix 4.A).

Policy 4: Extending the EITC credit plateau for married filers to equal at least the Official Poverty Measure (OPM) threshold for a two-adult household with a given number of dependents, while leaving the maximum wage at which married filers could claim an EITC unchanged in order to maintain the progressivity of the EITC (Figure 4.1E). As before our proposal would extend these schedule changes to all State EITC policies except those in California, Minnesota, Indiana, which did not follow a separate schedule for married (vs. single) filers, and DC, which did the same for those without dependents.

Policy 5: Extending the maximum EITC plateau credit for a given family size and composition to all those with any earned income, eliminating the EITC phase-in structure. This would make the EITC similar to most state CTC policies[229] and be explicitly designed to benefit those in deep poverty. It would likewise maintain or enhance the EITC work incentive given the EITC phase-in structure appears to have little or no incentivising effect on those already in work to increase their hours.[37] A more substantial version of this proposal would eliminate the EITC work requirement altogether. Unfortunately, as BRFSS does not collect information needed to differentiate those with little earned income and no earned income, our analysis blends both; overestimating the number of current low-income EITC recipients and under-estimating the number of new EITC recipients if work requirements were eliminated. As before, our proposal would extend these schedule changes to all State EITC policies except those in California, Minnesota, and Virginia, who explicitly set higher minimum earnings requirements in their EITC program.

4.2.2.3 Effect Modifiers

To understand how each of our proposals would reshape social equity, we repeated our analyses stratifying by interviewer-presumed sex (male or female), self-identified race (white, Black or African American (Black hereafter), American Indian or Alaska Native (NAAN hereafter), Asian), ethnicity (Hispanic or not), highest educational attainment (high school/received a General Educational Diploma (GED) or did not), and household poverty status (in poverty or not). We chose to dichotomize education at high school completion because most individuals with a bachelor's degree or higher earn more than the maximum income eligible for the EITC[230] and because high school completion is typically the most informative educational divide concerning health.[93] Our operationalization of household poverty status also requires further explanation.

BRFSS participants self-report their annual household income via bracketed response categories (e.g., less than $10,000, $10,000 to $15,000, etc.). We recognize the limitations of this measure, as it does not differentiate between different types of income (e.g., earned income, transfers, etc.), whether respondents had no earned income, or allow exact EITC credit eligibilities to be determined. To determine likely household poverty status, we first used within-category uniform imputation to impute continuous incomes for each respondent, then used imputed continuous incomes in determining individual credit eligibilities and household poverty status assuming reported incomes do not include transfers. This imputation approach has been shown to perform better than alternative simple imputation approaches at recreating the population income distribution for those with low-to-moderate-incomes when compared against continuous income data from the Current Population Survey (CPS).[94] We accounted for imputation uncertainty by repeating this process 500 times per respondent and using each imputed income serially across bootstrap repetitions of our analysis to generate outcome point estimates and confidence bounds (see Section 4.2.3.5). We based our household poverty measure on the Census Bureau Official Poverty Measure (OPM)[95] for each respondent's reported household size and composition. To account for differences in costs-of-living, however, we adjusted OPM thresholds by state before determining respondent poverty status using an established Median Rent Index (MRI)-based approach,[97] with nominal rent information taken from the 2019 American Community Survey (ACS).[231] We recognize the limitations of this measure, as it does not differentiate between different types of income (e.g., earned income, transfers, etc.), whether respondents had no earned income, or allow exact EITC credit eligibilities to be determined.

4.2.2.4 Confounding Variables

We accounted for several hypothesized individual- and state-level confounding factors when simulating the potential policy effects of EITC credit eligibility on individual FMD. We provide a short description of each below and a more extensive review of their coding in Appendix 4.B. We did not account for any confounding variables when examining our other outcomes, as these did not require isolating an exposure-outcome association.

Individual-Level: We adjusted for continuous respondent age (in years), current employment status (employed or unemployed), current home-ownership status (yes or no), and county rurality based on the National Center for Health Statistics (NCHS) Urban-Rural Classification Scheme. We likewise adjusted for other sources of income not related to the EITC such as imputed household income (presumed to not include transfers) and other state and federal credits simulated using the NBER TAXSIM 35 tax simulator model (e.g., the CTC, Additional CTC, Child

Care Credit, and State CTC).[190] Though presumed to confound our relationship of interest, we could not account for other income or in-kind transfers commonly received by EITC recipients such as Supplemental Nutritional Assistance Program (SNAP) benefits or Temporary Assistance for Needy Families (TANF),[232] as BRFSS does not directly ask respondents about their receipt of transfers and both programs have much lower participation rates, making receipt unreliable to impute.[233]

State-Level: We accounted for several state-level confounding factors related to population demographics, economic performance, political leadership, and labor and social assistance policy (see Appendix 4.B for source information). Demographic factors included state median age, population size, population proportions by race and ethnicity, proportions by educational attainment among those 25 years or older, proportion foreign-born, proportion living in urban census blocks, and proportion working in blue-collar roles among those aged 16 years or older based on the International Labor Organisation's (ILO) classification of International Standard Classification of Occupations 88 (ISCO-88) codes, which we mapped to 2010 Standard Occupational Classification (SOC) codes using Kouretsis and Bampouris' crosswalk.[234] Indicators of economic performance included Gross State Product (GSP) per capita, average annual seasonally adjusted state unemployment rates, proportion of households with incomes below the OPM for their size and composition, and proportion of working-aged adults 19-64 years old without health insurance coverage. Political leadership was measured using an index of state government political control,[235] reflecting the governor's party affiliation and upper and lower state legislature compositions by political affiliation. Finally, policy indicators included the state minimum wage, the maximum combined TANF and SNAP monthly benefit available to a three-person family, and an indicator for whether the state had expanded Medicaid coverage to those with low incomes since the Affordable Care Act (ACA). To account for high correlation between state-level covariates, we modelled these variables as a reduced set of principal components (see Section 4.2.3.2).

4.2.3 Statistical Analysis

4.2.3.1 Estimating EITC Credit Eligibilities Under Proposed Policy Reforms

We followed a multi-step process to estimate likely respondent EITC credit eligibilities under each of our proposed policy reforms. First, we created a dataset with records for every combination of household income from $0 to $60,000, marital status, number of dependents up to three, and state including DC. This was intended to cover all populations eligible for Federal or State EITCs under existing policy. We then formatted this dataset as-needed for the NBER TAXSIM 35 tax simulator model,[190] and used this model to simulate likely Federal and State EITC credit eligibilities for all records in the 2019 BRFSS. Unfortunately access to the NBER TAXSIM model itself is restricted to non-NBER affiliates, and so we could not use this model as a framework for simulating our policy proposals. We did, however, use these simulated credit amounts to recalculate all relevant EITC features necessary to create our own coding schema. These included state-specific maximum household incomes at which individuals are eligible for the maximum plateau credit or any credit, EITC phase-in and phase-out rates, maximum credit amounts, and 'adjustment factors' reflecting the proportions of the Federal EITC each State EITC matches. Next, we compared each feature against those reported in the UKCPR National Welfare Database and, where discrepancies arose, reviewed state tax codes to determine the appropriate value (see Appendix 4.A for related details). Using our derived coding schema, we then calculated what Federal and State EITC credit each record in our simulated dataset would likely be entitled to under each of our policy proposals, which simply required changing the set value of each EITC feature. We then matched each BRFSS respondent to the relevant record in our simulated dataset based on household income, marital status, and number of dependents to estimate their likely EITC credit eligibilities under our proposed policy reforms. As a final step, we manually reset credit eligibilities to zero where individuals would not be eligible for a Federal or State EITC based on their age. Due to lacking relevant information, however, we could not account for other eligibility rules concerning citizenship or whether individuals had a Social Security number (SSN), spousal ages, foreign income or investment income, and whether or not children can be counted as dependents. In all cases, we assumed eligibility criteria would be met.

4.2.3.2 Consolidating State-Level Confounder Information for Model Parsimony

We aimed to account for 26 state-level confounding factors when modelling the relationship between EITC credit eligibility and individual FMD. To avoid model convergence issues and high multicollinearity, we first used Principal Component Analysis (PCA) – a common method for dimension-reduction – to reduce these factors into a smaller number of ordered principal components each explaining distinct portions of the variance across original covariates.[236] We included all principal components with eigenvalues ≥ 1 (N=6), collectively explaining 81% of the variance across state-level confounding variables.

4.2.3.3 Estimating the Mental Health and Health Equity Impacts of Proposed Policy Reforms

To simulate the potential impacts of each of our policy proposals on individual FMD, we fit a cross-classified multilevel linear probability model of the relationship between EITC credit eligibility and individual FMD under existing policy and used this model to predict group-level FMD prevalence with and without substituting out existing respondent EITC credit eligibilities and state policy features with those implied under each of our proposals. Cross-classified models are an extension to standard multilevel modelling that allow for simultaneous, non-hierarchical group clustering between observations.[237,238] They are increasingly used in social science research[239] for a variety of purposes, such as accounting for complex non-independence, avoiding omitted variable bias,[240] or exploring how multiple contextual factors shape focal exposure-outcome relationships. In our case, respondents (level 1, *i*) are nested within states (level 2a, *j*) as well as within intersectionally defined social groups (i.e., groups defined by two or more social axes at once – in our case presumed sex, race, ethnicity, educational attainment, and household poverty status, level 2b, *k*), necessitating a cross-classified model structure. While this level 2b clustering design is also used in Intersectional Multilevel Analyses of Individual Heterogeneity and Discriminatory Accuracy (I-MAIHDA) which are a novel quantitative approach for understand complex sociodemographic inequalities,[241] we do not perform an I-MAIHDA. We clustered by intersectional social group theorizing that individuals occupy different positions in social hierarchies based on their multiple social identities (e.g., their race, their sex)[33,72] and that these contextual positions shape their access to economic resources,[242] opportunities,[73] and good mental health.[170] Meanwhile, we clustered by state because state economic conditions and policies are important contextual determinants of mental distress.[183] Our model is presented in Equation 1 below.

$$FMD_{ijk} = \beta_{0jk} + \sum_{n=1}^{16} \beta_n x_{nijk} + \sum_{l=1}^{3} \beta_{17(l)} B_l x_{17(l)ijk} + \sum_{l=1}^{3} \beta_{18(l)k} B_{lk} x_{18(l)ik} + \beta_{19k} x_{19ik} + \epsilon_{ijk},$$

$$\beta_{0jk} = \beta_0 + u_{0j} + u_{0k},\ \ \mu_{0j} \sim \mathcal{N}\left(0, \sigma_{u_j}^2\right),\ \ \mu_{0k} \sim \mathcal{N}\left(0, \sigma_{u_k}^2\right),\ \ \epsilon_{ijk} \sim \mathcal{N}(0, \sigma^2)$$

Fixed effects in our model included respondent presumed sex, self-identified race and ethnicity, highest educational attainment, and household poverty (β_{1-5}), an indicator for whether states had a funded, refundable State EITC policy in the prior year (β_6), and respondent- and state-level confounding factors (β_{7-17}). EITC credit eligibilities (β_{18}) and a categorical measure reflecting marital status and number of dependents (β_{19}) were also included as level 2b random effects, allowing the relationship between each and individual likelihoods of FMD to vary across intersectional groups. Non-EITC household income (β_{17}) and EITC credit eligibilities (β_{18}) were modelled as B-splines with three internal knots to allow the functional form of the income-FMD relationship to vary flexibly. Our model was fit via maximum likelihood estimation using the *glmmTMB* package[243] in R and incorporated BRFSS sampling weights.

4.2.3.4 Suppression of Unreliable Estimates

To avoid presenting unreliable outcome figures, we suppressed all estimates relating to groups with an actual or effective sample size accounting for design effects less than 10. We then suppressed all counts and proportions as appropriate following NCHS data presentation standards.[100,244] For counts, this involved censoring any estimate with 1) an actual or effective sample size accounting for design effects less than 10 or 2) a 95% Confidence Interval (CI) width more than 160% of the point-estimated value. For proportions, this involved censoring any estimate with 1) an actual or effective sample size less than 30, 2) a 95% CI wider than 0.3 in absolute value, 3) a 95% CI width more than 130% of the point-estimate, or 4) a point-estimate equal to zero or one, indicating every respondent was a case or non-case.

4.2.3.5 Confidence Intervals

We estimated percentile-based 95% CI for all estimates using a non-parametric stratified bootstrapping approach based on intersectional social group membership (i.e., based on presumed sex, race, ethnicity, educational attainment, and household poverty status). To do so, we 1) assigned individuals one of 500 imputed household incomes (see Section 4.2.2.3) and determined their household poverty status, 2) resampled respondents with replacement proportional to how common their presumed sex, race, ethnicity, educational attainment, and household poverty status were in combination within their state, then for each outcome 3) took the mean value across repetitions as our outcome point-estimate and 4) took the 2.5^{th} and 97.5^{th} percentile estimate as our lower and upper confidence limits.

All analyses were performed in R Version 4.4.1[245] using the RStudio IDE.[102]

4.3. Results

4.3.1 Study Population and Weighted Sample Characteristics Under Existing Policy

BRFSS interviewed 418,268 non-institutionalized adults in 2019, with 259,156 (62%) known to be aged 18-64 years old, 235,251 (56%) meeting demographic criteria for inclusion in our study, and 194,092 (83% of this eligible population) having complete information on all study variables and so included in our sample. Demographically, our unweighted sample was more often female (52%), non-Hispanic (93%), white (85%), high school graduates (95%), and not in poverty (86%) (Table 4.2). Likewise, most respondents were married (54%) and did not report having children under 18 years old living at home (61%). Finally, 40% of respondents lived in a state without any State EITC policy in the prior year, 11.3% lived in a state with only a non-refundable State EITC, and 49% lived in a state with a refundable State EITC policy.

Under existing Federal and State EITC policy, we estimate that 24.2% of our weighted sample (N=33.3M) were likely eligible to receive an EITC, with a median combined Federal and State EITC credit of $2474 [IQR: $464, $4556] (Table 4.3). Of this group, 52.2% (N=17.9M) were likely eligible to receive a State EITC with a median credit of $217 [IQR: $94, $589] (Table 4.3, Figure 4.2A, 4.2B). If all those eligible for an EITC received one, we estimate that this would result in 14.4% of those in poverty (N=3.5M) being lifted out of poverty, with most of this reduction due to the Federal EITC (Figure 4.2C). Owing to differences in household size, composition, and imputed income, a greater proportion of those female (vs. male), Hispanic (vs. non-Hispanic), self-identifying as Black or NAAN (vs. white), less educated (vs. more), and in household poverty (vs. not) were likely eligible to receive an EITC (Figure 4.2A). Typical EITC credit eligibilities also tended to be higher for all socially disadvantaged groups except by race, where credit eligibilities were similar (Figure 4.2B). As those from socially disadvantaged groups tend to be in deeper poverty, however, the EITC would lift a greater proportion of those more educated (vs. less) and white (vs. NAAN or Asian) out of poverty in our weighted sample (assuming equal likelihoods of EITC receipt), widening educational and racial inequities in poverty (Figure 4.2C).

Based on respondent's self-reported mental health, the average annual past-month prevalence of FMD in our weighted sample was 15.1% overall (95% CI: 14.8% to 15.4%) and 23.1% among those likely eligible for an EITC (95% CI: 22.4% to 23.8%) (Table 4.3). FMD prevalences were higher among those eligible for an EITC in all social groups except those Hispanic, less educated, and in poverty, where prevalences were comparable. Comparing social groups, FMD prevalence was consistently lowest for those Asian (Overall FMD Prevalence 10.4%, 95% CI: 8.5% to 12.4%. EITC-Eligible FMD Prevalence 13.4%, 95% CI: 9.4% to 17.9%) and highest for those in poverty overall (FMD Prevalence 25.7%, 95% CI: 24.5% to 27.1%) or non-Hispanic among those likely eligible for an EITC (FMD Prevalence 25.8%, 95% CI: 24.8% to 26.9%) (Figure 4.2D). Observed and estimated FMD prevalences were similar in all cases (Table 4.3), with point estimates differing by at most 0.3%.

4.3.2 Economic Impacts of Proposed Policy Reforms

4.3.2.1 Combined, Federal, and State EITC Expenditures

Across our weighted sample, the tax expenditure of the Federal EITC in 2019 was $68.0B and of all State EITC policies was $6.3B (Table 4.3). While Federal and State EITC tax expenditures would increase under all our proposed policy reforms, the cost of these expansions as well as who would pay for them varies. Expanding State EITC availability and refundability nationwide (policy 1), for example, would increase state-level EITC tax expenditures by the greatest extent (+$4.6B), though understandably these costs would be restricted to states without existing refundable policies and have no impact on Federal EITC expenditures (Table 4.3). Otherwise, expanding the "childless" EITC (policy 3) or eliminating the EITC phase-in structure (policy 5) would be the most expensive changes at federal and state levels, raising nationwide EITC expenditures from approximately \$74.3B to \$83.1B dollars (policy 3, +\$8.8B) or \$82.9B (policy 5, +\$8.6B). Increasing the generosity of the EITC by 10% for all filers (policy 2) would also raise EITC costs considerably (Federal: \$74.8B, +\$6.8B, State: \$6.8B, +\$0.5B), though to a slightly smaller extent. Finally, by comparison, extending the credit plateau for married filers (policy 3) would only result in a modest increase in tax expenditure (Federal: \$69.5B, +\$1.5B, State: \$6.4B, +\$0.1B).

4.3.2.2 Individual Federal and State EITC Eligibility

When comparing the simulated impacts of our proposals on economic wellbeing and social equity, we focus on how each increases EITC benefits along the income distribution (Figure 4.3A), expands EITC access (Figure 4.3B), reshapes the distribution of EITC credit eligibilities (Figure 4.3C-E), and lessens poverty (Figure 4.3F) overall and by social group.

In Figure 4.3A, we plot the population-weighted local average change in combined Federal and State EITC credit eligibility for each proposal compared to existing policy according to household income. Based on this figure we find that eliminating the EITC phase-in structure (policy 5) would be the most progressive policy change, increasing EITC benefits for the lowest-earning households by over \$2500 on average and by as much as \$9178 on an individual basis. By contrast, extending the credit plateau for married filers (policy 4) would be the 'least' progressive, with most benefits going to those with incomes over \$25,000. Expanding the "childless" EITC (policy 3) would also skew towards helping lower-earning households more, while expanding refundable State EITC availability (policy 1) and increasing the generosity of the EITC by 10% (policy 2) would distribute benefits broadly, with policy 3 providing larger increases in EITC credit eligibility on-average. How each in-turn affects social equity depends on group differences in household income distributions and family compositions as well as on the number of individuals made newly eligible for an EITC.

In terms of broadening EITC access, only expanding refundable State EITC availability (policy 1) and expanding the "childless" EITC (policy 3) would affect the size of populations eligible for an EITC (Table 4.3, Figure 4.3B). Comparing these policies, we find that expanding refundable State EITC availability nationwide (policy 1) would have the largest impact of all policies, increasing the overall percentage eligible for a State EITC policy by 83% or 10.5 percentage-points (pp) to 23.2% (95% CI: 22.8%, 23.5%). Due to socio-geographic variation in where groups live, where State EITC policies were available in 2019, and who is typically eligible for an EITC (Figure 4.2A), this nationwide expansion would disproportionately benefit women, those Hispanic, Black or NAAN, less educated, or in poverty, with those in poverty seeing the largest increase in access. Expanding the "childless" EITC (policy 3) would also increase EITC availability significantly by 5.4% if implemented federally or 2.1% if implemented in all states, with fewer social differences in who gains access.

As most of the proposals we examine target select population groups (e.g., those without dependents for policy 3 or married filers for policy 4), most individuals would see little change in their eligible EITC across our proposals except under policy 2 (increasing the generosity of the EITC by 10%), where the median individual would see their EITC increase by $252. For this reason, we focus in Table 4.3 and Figure 4.3C-E on summarizing how our proposals would change the distribution of EITC credit eligibilities among those likely already eligible for an EITC. When interpreting these estimates, however, it is important to keep in mind that as some proposals shift where individuals fall along the credit distribution, these differences cannot be interpreted as individual-level changes in credit size. We find that expanding the "childless" EITC (policy 3) would have the largest impact on raising the 'floor' of EITC benefits, increasing the 25^{th} percentile credit from $464 to $1172 (+$708) (Table 4.3) with larger increases for those less educated (+$786) or in poverty (+$881). By contrast, all other policies would have substantially smaller impacts on the lower tail of the EITC credit distribution except eliminating the EITC phase-in (policy 1) for Hispanics, whose 25th percentile credit would increase by $185. When focusing on how each policy would change the median or 75th percentile credit individuals are entitled to, we see broadly the same pattern across policies. In both cases we find that eliminating the EITC phase-in (policy 5) would have the largest impact on typical EITC credit eligibilities, raising the median EITC credit by $497 and the 75th percentile credit by $733 (Table 4.3). In each case those female, Black, NAAN, or less educated would see the largest increase in eligible credits. Increasing the generosity of the EITC by 10% (policy 2) and to a lesser extent the introduction of refundable State EITC policies nationwide (policy 1) would also raise median and 75th percentile credit eligibilities substantially, with greater increases across most socially disadvantaged groups including those in poverty.

The overall impact of each proposal on individual economic wellbeing and social equity depends on how they expand EITC availability, how and where they raise credit eligibilities, and who these policies preferentially benefit. To summarize the simulated economic impacts of each policy, we assessed how many additional people they would lift out of poverty compared to existing policy in Table 4.3 and Figure 4.3F. In doing so, we find that expanding the “childless” EITC (policy 3) would be the most effective change for reducing poverty in absolute terms, lifting an additional 3.2pp of those in poverty out compared to existing policy and between 1.6 to 3.9pp of those in poverty out across social groups. Increasing the generosity of the EITC by 10% (policy 2) and introducing refundable State EITC policies nationwide (policy 1) would also be effective, lifting an additional 1.6pp and 1.0pp of those in poverty out compared to existing policy respectively. While most of these policies had no considerable impact on absolute social inequities in poverty status, it is worth noting that expanding the “childless” EITC (policy 3) would tend to widen absolute social inequities in poverty status by lifting greater proportions of those male (vs. female), non-Hispanic (vs. Hispanic), White (vs. Black, Asian, or NAAN), and more educated (vs. less) out of poverty. Likewise, all policies we explore would tend to widen social inequities in poverty status defined multiplicatively since socially disadvantaged groups would see comparable if not smaller absolute reductions in poverty despite having proportionally more people living in poverty.

4.3.3 Health and Health Equity Impacts of Proposed Policy Reforms

Counter to expectations, we do not estimate any difference in FMD prevalence associated with our policy proposals overall (Table 4.3) or when stratifying by social group (Figure 4.4). We likewise do not observe any difference in FMD prevalences when restricting to those likely eligible to receive an EITC under existing policy, suggesting our results are not due to the small size of affected groups (Table 4.3, Figure 4.4). Of note, however, we could not assess the expected mental health impacts of introducing a refundable State EITC policy nationwide (policy 1) for any group, as in all cases prevalence estimates were statistically unreliable and so censored following NCHS guidelines.

4.4. Discussion

4.4.1 Comparing Our Findings to the Existing Literature

Despite the importance of EITC policies for supporting low- and middle-income workers, these policies currently fall short of their potential to alleviate poverty and advance social equity. To this end, our study simulated the potential impacts of five previously proposed Federal and State EITC policy reforms on national EITC expenditures, typical EITC credit eligibilities, numbers lifted out of poverty, and population mental distress compared to existing policy in 2019. With an eye to improving social equity in US tax and social assistance policy, we also examined who would benefit from each policy by sex, race, ethnicity, educational attainment, and household poverty status. We found that every policy would improve EITC availability or generosity for at least some social groups but vary in their effectiveness towards reducing poverty and narrowing social inequities. Eliminating the EITC phase-in structure, for example, would be the most progressive policy change, raise typical credit eligibilities by the greatest extent, and lessen social inequities in income considerably. However, it would have little impact on lifting people out of poverty given those benefiting live further below the poverty line. Expanding the “childless” EITC by contrast would extend EITC benefits to the greatest number of new people and lift the most additional people out of poverty across groups but tend to widen social inequities through disproportionately benefiting those male, non-Hispanic, white, and more educated. Increasing the generosity of the EITC by 10% and expanding refundable State EITC policy availability nationwide would also have considerable impacts on raising typical credit eligibilities, lifting people out of poverty, and lessening social inequities in income, but have little impact on social inequities in poverty. In contrast, based on our findings extending the credit plateau for married filers would make the EITC less progressive, have limited impact on typical credit eligibilities, lift relatively few additional households out of poverty, and slightly worsen social inequities in income. Unfortunately, our findings also suggested that none of the policies we examined would meaningfully improve population mental distress at the group-level beyond that already accomplished by the EITC in its current form. Finally, our results suggested that each policy would raise Federal EITC tax expenditures by $1.5 to $8.1 billion dollars if at all and State EITC expenditures by $0.1 to $4.5 billion dollars nationally, though as we will discuss these costs are somewhat overestimated.

One of the main findings from our analysis was that increasing the generosity of the EITC, whether overall or for specific demographic groups, could lift several hundred thousand additional households out of poverty and increase incomes for millions more. These findings qualitatively agree with those reached in the existing literature. For example, Hoynes *et al.* estimated that increasing Federal EITC generosity by 10% in 2017 would raise average credit eligibilities by $246 and lift an additional 300,000 adults out of poverty.[246] This closely matches our estimated average credit increase under the same proposal at $252 but simulates a smaller reduction in poverty than we do at 380,000 households. This will partly be because we overestimate the number of households living in poverty. Pac *et al.* also conducted a similar analysis to ours, simulating the potential effect on child poverty if all states implemented a refundable State EITC policy matching the most generous percentage of the Federal EITC of any state at the time (43% in Wisconsin).[247] Under this proposal they found child poverty would fall by 0.6% to 1.5% depending on the baseline poverty status of the state. This is similar to our estimated reduction in household poverty at 1.0%, although our expansion only introduced State EITC policies matching 15-17% of the Federal EITC instead of 43%. As might be expected, research also suggests that increasing EITC generosity more would result in larger reductions in poverty. For example, the National Academy of Sciences, Engineering, and Medicine (NASEM) in their 2019 report “A Roadmap to Reducing Child Poverty” found increasing the generosity of the EITC by 40% would reduce the number of children in poverty by 690,000 without counting employment effects or 1.55M when additionally modelling EITC-induced changes in employment,[248] which are both much larger than our estimated reduction. Likewise, based on an analysis of the 1993 Federal EITC expansion which raised EITC generosities by 10-30%, Hoynes and Patel[213] found that a $1000 increase in the EITC in 2015 dollars would reduce the share of households in poverty by 8.4%. Our proposal by contrast would only reduce the share of households in poverty by 1.5%.

Our study also finds that while expanding the “childless” EITC would be the most effective single reform for reducing poverty in most social groups, it would also widen social inequities in income and poverty. Although policymakers may consider this an acceptable negative consequence if their goal is primarily to improve economic wellbeing (as opposed to minimize social inequities), we believe it is nevertheless important to highlight. Our findings are corroborated by recent literature examining the economic impacts of the temporary expansion to the “childless” EITC under ARPA. For example, Crandall-Hollick *et al.*[249] found that ARPA extended Federal EITC benefits to 7.5 million additional households, raised average credit eligibilities for childless workers by $524, and raised tax expenditure associated with the Federal EITC by $10.0 billion dollars, while Wimer and Curran[250] found ARPA reduced the share of young adults in poverty by

3.3% with greater benefits for those white and more educated. By comparison, our study found that an ARPA-like expansion would extend Federal EITC benefits to 7.7 million additional households, raise average credit eligibilities for childless workers by $514, increase tax expenditure by $8.1 billion dollars, and reduce the share of households in poverty by 3.2% with greater benefits for those white, more educated, non-Hispanic, and male. Of note, while Crandall-Hollick *et al.*[249] and Wimer and Curran[250] both relied on individual tax return data for their analyses, we did not, suggesting our income imputation approach is a valid alternative for exploring the economic and health impacts of EITC reform.

An important counter-intuitive finding from our analysis was that none of the policy reforms we examined would likely improve population mental distress. While this could be for artefactual reasons such as non-differential misclassification of our exposure, unmeasured confounding (e.g., by individual SNAP or TANF receipt), our assumed causal model differing from reality, our cross-sectional study failing to identify important time-varying effects, or our model being otherwise mis-specified, it is also consistent with the mixed literature examining the mental health effects of EITC policies generally. For example, Morgan and colleagues examined the potential impacts of a 10% increase in State EITC generosity on mental distress, depression, and suicidal behavior using different methodologies, and found small but sometimes significant improvements across outcomes[185,186,251]. Meanwhile, Courtin *et al.* and Muennig *et al.* examined the impacts of the Paycheck Plus experiment, which quadrupled Federal EITC generosity for low-income filers without dependents in New York City and Atlanta, and reached mixed findings. They found significant improvements in psychological distress in one study,[252] no impacts on anxiety or depression in another,[253] and significantly worse depression and psychological distress in a third;[254] although quantitative bias analyses by Muennig *et al.* suggest differential nonresponse bias could explain their negative findings. Based on this, our study suggests more causally robust research is need to understand when and for whom EITC policies improve mental health. For example, this discrepancy could be because mental health is multifaceted and some but not all outcomes are improved by EITC receipt, because EITC benefits are modest and so sometimes not detected, or because EITC policies as implemented only improve mental health for certain demographic groups (e.g., those with dependents) or when other supports are in place (e.g., improved health care access).

Finally, our study suggests that extending the credit plateau for married filers would provide minimal benefit to most households while widening social inequities in income. As the US Department of Health and Human Services recently published a white paper exploring how to address marriage penalties in means-tested transfer programs including the EITC,[28] this is particularly relevant to policymakers. Prior to our analysis, several proposals had been made on how to address marriage penalties in the EITC including raising the maximum credit for married filers, replacing the EITC with a 'Working Parent's Wage Supplement', and extending the wage at which the EITC begins to phase-out, with or without also raising the maximum credit at which households are eligible for any EITC.[28] As extending the credit plateau for married filers while keeping the maximum credit unchanged is arguably the most progressive and targeted option among these proposals, however, our findings suggest this may be difficult while concurrently prioritizing social equity.

4.4.2 Strengths and Limitations

Readers may have valid concerns over how realistic our findings are given we rely on household survey data which typically underestimates EITC recipiency,[255] a tax simulator which has been known to overestimate the poverty-alleviating impact of the EITC,[256] and an imperfect measure of household income. We hope to allay those concerns, while noting where our findings should be interpreted with caution. First, while our study somewhat overestimates the cost of the Federal EITC at $68.0B compared to the actual figure at $64.5B,[36] this is still broadly in line with that estimated by the Congressional Joint Committee on Taxation at $70.0B[257] and so is a reasonable basis for cost comparisons. Likewise, despite our imperfect income measure, we simulate the distribution of average Federal EITC credit eligibilities well based on IRS figures with less than a 5% discrepancy at all points along the earnings distribution.[258] However, our study does meaningfully overestimate the number likely eligible for an EITC at 32.6M compared to the actual number of eligible filers at 26.5M,[258] with greater overcounting among households with multiple dependents. This is likely because we could not differentiate between households with no earned income, who are ineligible for the EITC, and those with low earned incomes. As roughly 6% of households have no earned income,[37] this could partly explain our discrepancy. We expect any bias resulting from this would be greater for socially disadvantaged groups since they constitute a greater share of those out of work,[259] of those with no earned income,[37] and of households with multiple dependents (Table 4.2). Our study also likely overestimates the cost and under-estimates the economic and social equity impact of eliminating EITC work requirements and the EITC phase-in structure, since households without any earned income would be some of the main beneficiaries of this proposal yet are already simulated as receiving an EITC under existing policy.

There are also other important limitations of our study that should be noted. First, our analysis does not account for any behavioral or labor supply changes that may occur in response to our proposals. For example, while evidence suggests the EITC does not meaningfully incentivize those already in work to increase their hours,[37] eliminating the EITC phase-in structure could lead workers to decrease their hours and in turn see a smaller gain in income. Likewise, as evidence suggests the EITC subsidizes low-wage labor and leads to lower wage growth among non-recipients through increased competition,[260,261] if our proposals incentivize employment this could have negative impacts for low-wage workers already in employment, regardless of their EITC recipiency. However, this could be partly addressed by strengthening the minimum wage alongside expanding the EITC.[246,262,263] Separately, as our study is based on a cross-sectional household survey, we would caution against interpreting our simulated effects on population mental distress causally. While we do make substantial efforts to account for individual- and state-level confounding variables, this is not the same as longitudinal individual follow-up. Additionally, as we assume full EITC take-up in all comparisons except when looking at EITC tax expenditures, our estimates should be interpreted as upper limits of what could be achieved instead of likely changes in poverty or mental distress. As research suggests those Hispanic, NAAN and in poverty are less likely to file a tax return[204] or claim an EITC when eligible,[203,264] we expect this would overestimate the practical benefits of our reforms for these socially disadvantaged groups. Additionally, while we opt to use a complete-case sample to avoid complicating our analysis further, this decision could bias our findings if those included differed meaningfully from those not included. However, comparing included and excluded populations with known information we did not observe any meaningful differences across study variables.

Despite these limitations, we believe our findings address important gaps in the literature on EITC policy reform and offer novel insights for policymakers looking to improve the effectiveness and equity of EITC policies. For example, while many EITC reforms have been proposed and advocated for on a theoretical basis, these proposals have often lacked accompanying empirical analyses evaluating their costs and likely impacts. Relatedly, as empirical analyses often vary in their target populations, methodologies, outcomes, and analytic periods, this makes it difficult to compare implied costs and benefits across analyses. Our study addresses these issues by comparing the likely costs and impacts of five policy reforms using the same analytic approach, sample, and set of outcome measures. Separately, few empirical analyses have explicitly considered who would benefit from EITC reforms or the implications this has for social and economic inequality. In this respect our analysis adds substantially to the literature by indicating that expanding the “childless” EITC and extending the married filer credit plateau could worsen social inequities in income and poverty, while eliminating the EITC phase-in structure, increasing the generosity of the EITC, and increasing the availability of refundable State EITC policies would all be expected to narrow social inequities in income. Finally, while several studies have examined the mental health impacts of EITC availability,[185] generosity,[184,187] and recipiency[182] as well as of historical EITC reforms,[265,266] to our knowledge our study is the first to simulate how unenacted, potential EITC reforms could improve population mental health.

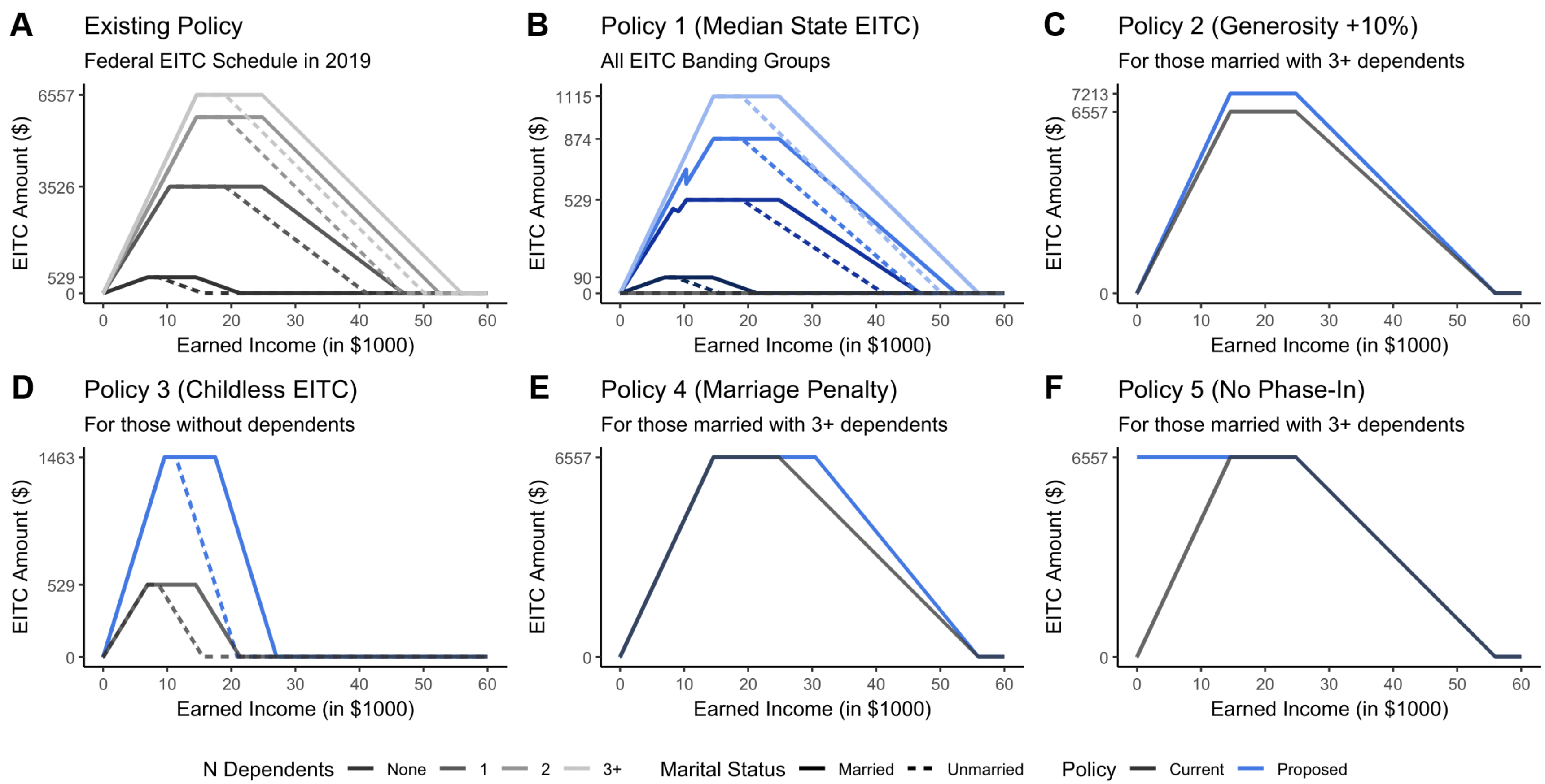
4.4.3 Future Research and Policy Implications

Looking forward, our findings support several avenues of research. First, while our study identifies sizeable benefits associated with most of the EITC reforms we assess, future research is needed to understand the behavioral and labor supply impacts of these reforms. As shown by NASEM in the context of a 40% increase in EITC generosity,[248] the indirect effects of expanding EITC policies on reducing poverty could be greater than their direct effects. Separately, our analysis supports additional research simulating the economic impacts of eliminating EITC work requirements and the EITC phase-in structure for those unemployed. Although we likely underestimated the impacts of this reform, we still found it would raise typical credit eligibilities substantially and do the most of any policy to address social inequities in income. Further, based on our review of the literature we did not identify any prior study considering this reform. This analysis for example could be accomplished using respondent data from the Current Population Survey Annual Social and Economic Supplement (CPS-ASEC) which has been linked to individual tax return data from the IRS, addressing many of the limitations of our analysis. Relatedly, as one of the largest limitations of our study was our inability to identify who received an EITC or how EITC take-up is socially distributed, future research should seek to understand social inequities in EITC take-up and quantify its impacts on socioeconomic inequities more generally. While some research already exists on this topic[201,203,264] this research has focused on individual states, indicating there is a need for national analyses. Finally, as we simulated no likely impact of any of our EITC reforms on population mental distress, our findings underscore the need for more causally robust research to understand how, if at all, EITC policies affect mental health. This is especially pertinent given the need to identify effective policy approaches for combating rising mental distress and widening social inequities in mental distress.[170]

Our results also have important implications for policymakers looking to improve the effectiveness and equitability of EITC policies. First, we expect that increasing the generosity of the EITC is likely an effective approach for reducing poverty and addressing social and economic inequality. Second, we expect that while expanding the “childless” EITC will effectively alleviate poverty, it will also disproportionately benefit socially advantaged groups and so require concurrent interventions to avoid worsening social inequities if this is also a priority for policymakers. Third, we expect that addressing marriage penalties while maintaining the progressivity and equitability of the EITC will be challenging, and that extending the credit plateau for married filers is unlikely to be an effective approach at accomplishing these twin goals. Fourth, we expect eliminating the EITC phase-in structure – with or without also eliminating EITC work requirements – would be a particularly effective approach for reducing social inequities in income. However, we also note additional research is needed to understand the likely behavioral and labor supply effects of such a reform. Finally, we expect that expanding State EITC policy availability, generosity, and refundability would meaningfully reduce poverty and improve social and economic equality even without any concurrent change in Federal EITC policy.

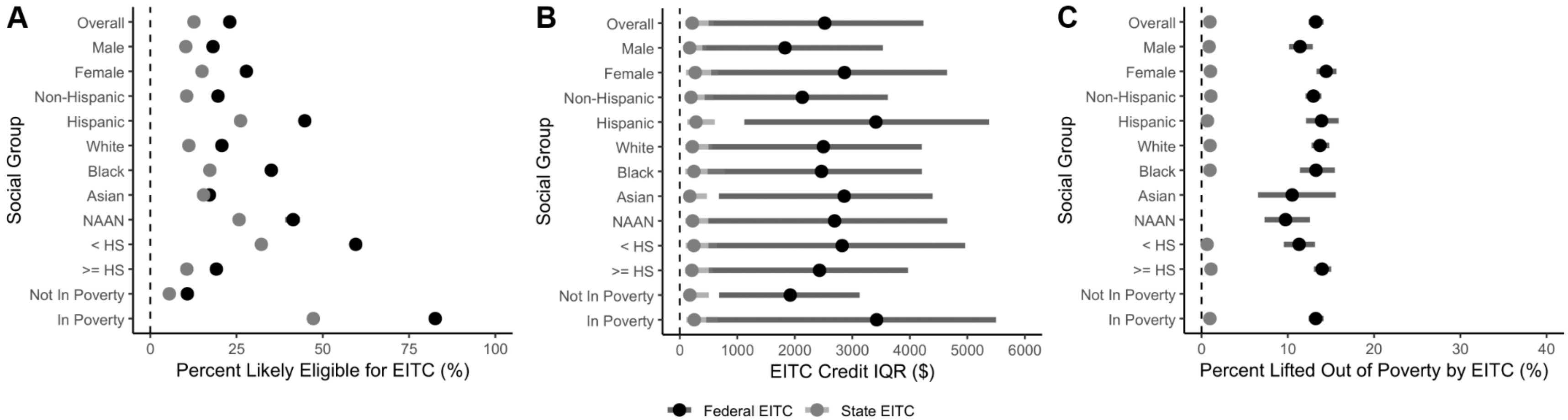
4.5 Relevant Tables and Figures

Figure 4.1. Federal and State EITC Schedules Under Existing Policy and Policy Proposals, BRFSS 2019.



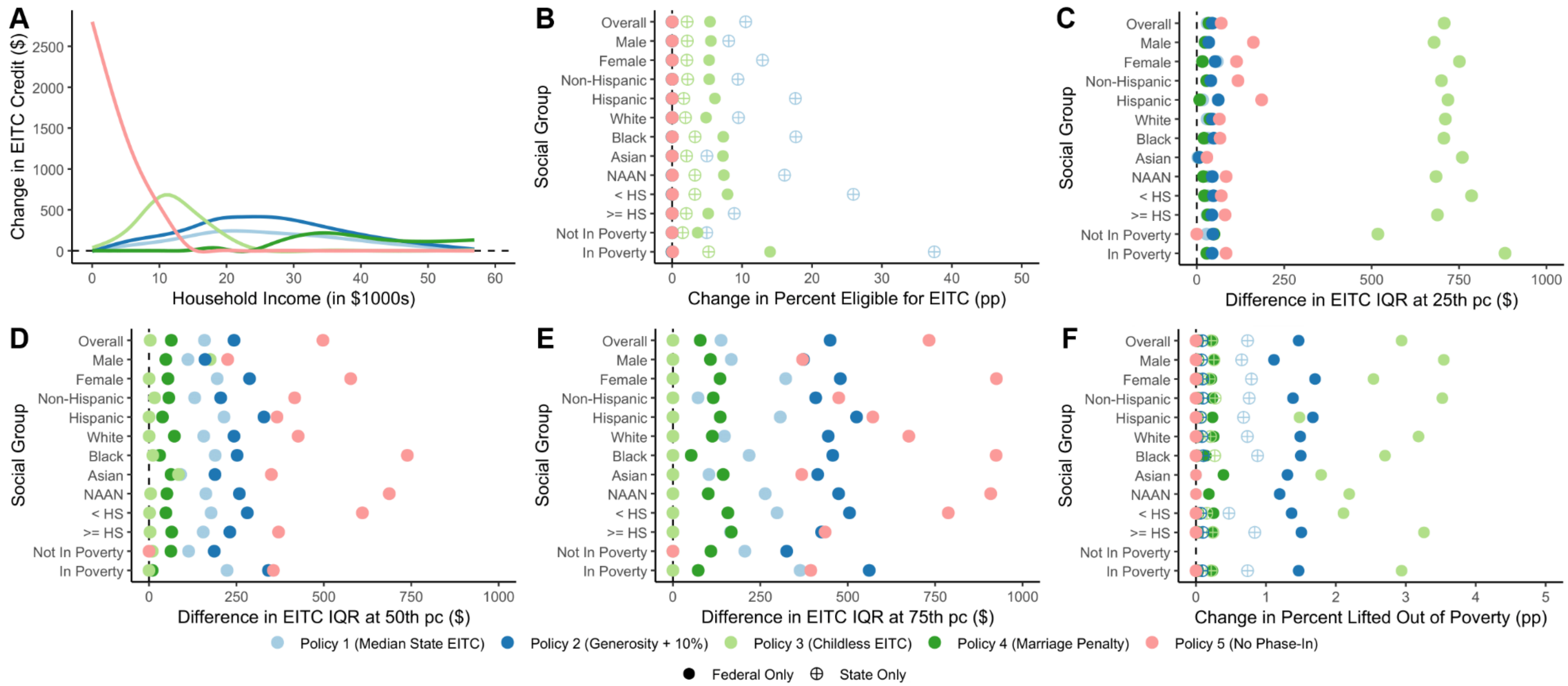
Legend. EITC: Earned Income Tax Credit. Note: EITC schedules for policies 2, 4, and 5 are restricted to EITC banding group subsets for illustrative purposes. In all cases, similar schedule changes occur for those with fewer dependents (policy 2, 4, 5) or unmarried (policy 2, 5).

Figure 4.2. Estimated Federal and State EITC Eligibilities, Numbers Lifted Out of Poverty, and Credit Sizes Under Existing Policy, BRFSS 2019.



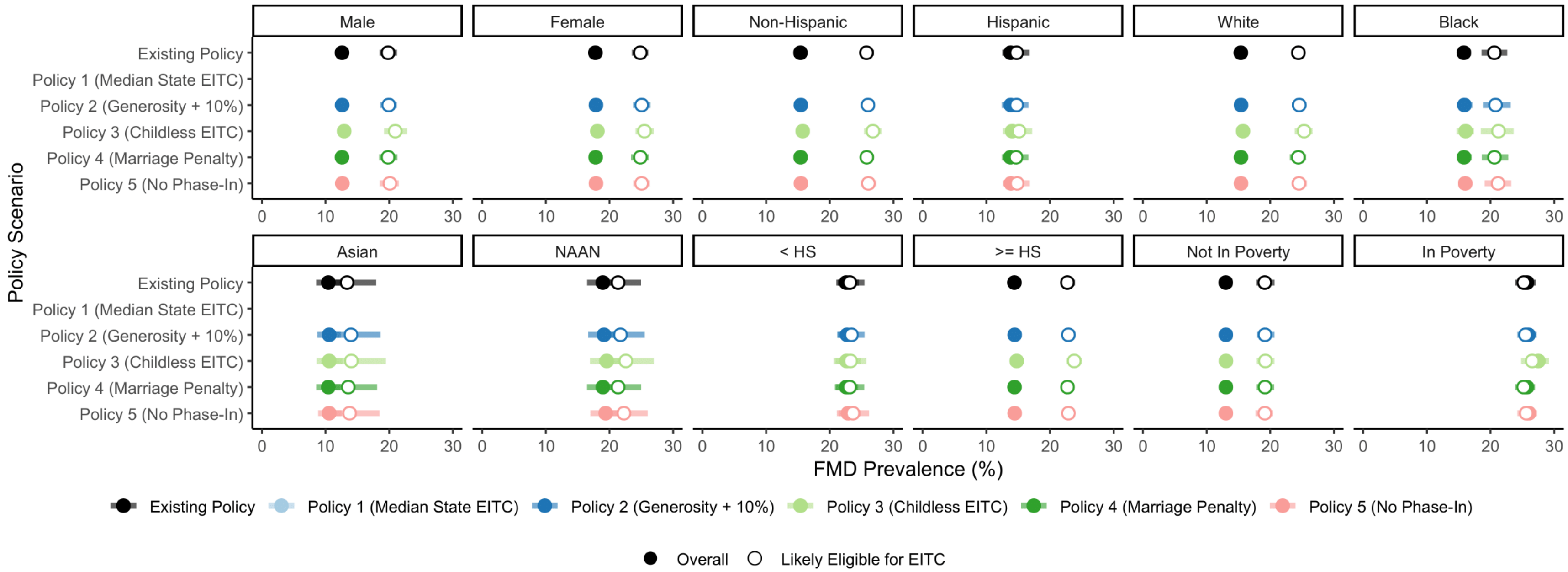
Legend. EITC: Earned Income Tax Credit. IQR: Inter-Quartile Range. Panel A: Within-group percentages likely eligible for an EITC credit. Panel B: Within-group percentages of those living in household poverty based on imputed household income alone lifted out of poverty when additionally counting likely Federal or State EITC credit eligibility towards poverty determination. Panel C: The inter-quartile range of Federal and State EITC credit eligibilities under existing policy. Error bars in panels A and B are 95% CI, while error bars in panel C represent the 25th and 50th percentile value of within-group EITC credit size distributions.

Figure 4.3. Simulated Economic Impacts of Policy Proposals Compared to Existing Policy, BRFSS 2019.



Legend. EITC: Earned Income Tax Credit. NAAN: Native American or Alaska Native. HS: High School or GED. Panel A: The population-weighted change in combined EITC credit eligibility among those already eligible for an EITC under existing policy. Panel B: The within-group absolute change in percentages likely eligible for a Federal or State EITC credit. Panel C-E: The difference in the 25th, 50th, and 75th percentiles of likely total EITC credit eligibilities for those already likely eligible for an EITC under existing policy. Panel F: The change in the within-group percentage of those living in household poverty based on imputed household income alone lifted out of poverty when additionally counting likely Federal or State EITC credit eligibility towards poverty determination. Note: The bottom legend (Federal Only, State Only) only applies to panels B and F. Panels A and C-E do not stratify based on EITC source for clarity. The dashed line in each panel indicates no difference compared to existing policy. Panel A is based on one of 500 bootstrap repetitions and so in theory these distributions could differ across bootstraps. Based on a random sample of 10 bootstrap repetitions, however, the shape of each distribution appears identical.

Figure 4.4. Average Annual Past-Month FMD Prevalence by Social Group, Likely EITC Credit Eligibility and Policy Context, BRFSS 2019.



Legend. EITC: Earned Income Tax Credit. NAAN: Native American or Alaska Native. HS: High School or GED. Error bars reflect 95% Confidence Intervals. All prevalence estimates were suppressed under policy 1 due to being statistically unreliable following NCHS guidelines.

Table 4.1. Tax Equity Concerns for Federal and State EITC Policies.

Tax Equity Concern	Explanation of Issue	Addressed in Study
Limited State EITC Availability	As of 2024, 19 states had not implemented a State EITC policy. This is despite strong evidence that EITC policies increase employment,[37] reduce poverty,[213] improve health[185] and educational outcomes,[267] and increase Federal EITC claims.[268] State EITC policies are also crucial in offsetting income and payroll taxes for low-income workers, which most regressive state tax codes rely upon. Further, while EITC policies are a large tax expenditure, they are also a net economic multiplier[269,270] and have been shown to largely pay for themselves over a sufficient economic window.[271]	Yes (Policy 1)
State EITC Non-Refundability	As of 2024, six states offered partially refundable or non-refundable State EITC policies, meaning EITC claimants do not receive a cash refund if their total taxes owed are less than their eligible credit. As EITC-eligible filers typically have low tax liability, non-refundable credits provide limited benefit to claimants. For example, while a married filer with three children earning the minimum plateau wage in Utah ($14,571) would in-theory be eligible for a $1,332 State EITC in 2023, their effective State EITC would only be $426 reflecting their total states taxes owed.	Yes (Policy 1)
Limited Federal and State EITC Generosity	While the Federal EITC does provide substantial benefits to most claimants averaging $2,541 per claim in 2022, research suggests increasing the generosity of the EITC would bring additional economic, health and social benefits, particularly for children of claimants.[248,272] There is also significant room to expand State EITC policies, as most states match a relatively low percentage of the Federal EITC, averaging 22% in 2022 across states with refundable policies.	Yes (Policy 2)
Limited "Childless" EITC Availability and Generosity	The Federal EITC and most State EITC policies offer substantially smaller benefits to "childless" workers (i.e. those without resident dependent children, including non-custodial parents). The EITC for "childless" filers has a slower phase-in and phase-out rate, a shorter plateau period, and a substantially lower maximum credit ($632 vs. $4,213 for those with one child in 2024). As a result, while half of all adults under 50 years old do not have children,[273] only 3% of EITC benefits go to "childless" workers.[274] The EITC for "childless" workers also restricts eligibility to those aged 25-64 years old, unlike the EITC for filers with dependents, raising equity concerns. For example, younger adults are increasingly likely to be unemployed[259] – which the EITC would disincentivise – and a growing segment of the population work past retirement age.[275] These differences curtail the poverty-alleviating effect of the EITC for younger workers and racially minoritized groups and contributes to "childless" workers being the only low-income group made worse-off by the tax system.[276]	Yes (Policy 3)
EITC Penalties for Married Filers	Marriage penalties and bonuses – where a couple filing as married are eligible for a smaller or larger combined transfer than if they were filing separately – are common in means-tested policies including the EITC.[28] These penalties and bonuses contribute to widening racial inequity as penalties most often occur where two low-income workers marry, which is much more common in Black and Hispanic families, and bonuses most often occur where one middle-income worker marries a non-worker, which is more common in white families.[27,277] For example, for a couple jointly earning $40,000 with two children in 2021, filing as married would lower their eligible EITC by $2959 if income was split evenly but raise their EITC by $1253 if only one individual worked.	Yes (Policy 4)
The EITC Phase-In Period and Work Requirement	Like most means-tested benefits in the US,[278] EITC eligibility is contingent on paid work, increasing in value as earnings rise. While work requirements increase employment among single mothers[255] and this has a multiplicative effect on household income through raising earned income,[263] this change in employment is modest, and negative in the case of married mothers. For those entering employment, a large portion of added income is typically spent on childcare.[279] By requiring work and increasing credit size with earnings, the EITC also provides little support to those in deep poverty[213] who are often unemployed, disabled, racially minoritized, or live in rural areas where securing employment is difficult.[280] As a result, the EITC only modestly lessens child poverty.[248] Evidence also suggests work requirements can reduce means-tested program participation[281] and depresses wages for low-skilled workers by increasing labor supply.[261]	Yes (Policy 5)

EITC: Earned Income Tax Credit. IRS: Internal Revenue Service.

Table 4.2. Sample size, unweighted percent and population weighted, BRFSS 2019.

Population		N (sample %, population-weighted %)								
		All	Single/Cohabiting				Married			
			0 dep.	1 dep.	2 dep.	3+ dep.	0 dep.	1 dep.	2 dep.	3+ dep.
	Overall	194,092 (100, 100)	62,987 (32.5, 32.3)	12,202 (6.3, 7.6)	7936 (4.1, 5.1)	5375 (2.8, 3.6)	55,101 (28.4, 23.3)	18,131 (9.3, 9.9)	19,078 (9.8, 10.9)	13,281 (6.8, 7.3)
Presumed Sex	Male	92,442 (47.6, 49.9)	33,371 (36.1, 36.5)	4700 (5.1, 6.4)	2821 (3.0, 3.8)	1810 (2.0, 2.6)	25,695 (27.8, 23.1)	8704 (9.4, 10.0)	9162 (9.9, 10.8)	6178 (6.7, 6.9)
	Female	101,650 (52.4, 50.1)	29,616 (29.1, 28.1)	7502 (7.4, 8.8)	5115 (5.0, 6.3)	3565 (3.5, 4.5)	29,406 (28.9, 23.6)	9427 (9.3, 9.9)	9915 (9.7, 11.0)	7104 (7.0, 7.7)
Self-Identified Ethnicity	Non-Hispanic	180,521 (93.0, 86.5)	59,045 (32.7, 33.0)	10,820 (6.0, 7.2)	6858 (3.8, 4.6)	4473 (2.5, 2.9)	52,850 (29.3, 24.8)	16,794 (9.3, 9.9)	17,635 (9.8, 10.8)	12,047 (6.7, 6.8)
	Hispanic	13,572 (7.0, 13.5)	3943 (29.1, 27.4)	1382 (10.2, 10.4)	1078 (7.9, 8.3)	903 (6.7, 7.6)	2251 (16.6, 14.1)	1337 (9.9, 10.1)	1443 (10.6, 11.5)	1234 (9.1, 10.7)
Self-Identified Race	White	164,064 (84.5, 76.9)	50,969 (31.1, 30.4)	9088 (5.5, 6.7)	5898 (3.6, 4.5)	3614 (2.2, 3.0)	49,953 (30.4, 25.5)	15,846 (9.7, 10.5)	16,845 (10.3, 11.5)	11,851 (7.2, 7.9)
	Black	18,763 (9.7, 14.4)	7885 (42.0, 38.9)	2243 (12.0, 12.7)	1461 (7.8, 8.8)	1177 (6.3, 6.8)	2959 (15.8, 14.5)	1193 (6.4, 6.5)	1085 (5.8, 6.7)	760 (4.0, 5.1)
	Asian	5926 (3.1, 6.5)	2226 (37.6, 37.9)	336 (5.7, 6.3)	171 (2.9, 2.8)	108 (1.8, 1.7)	1294 (21.8, 20.0)	704 (11.9, 11.8)	800 (13.5, 14.0)	288 (4.9, 5.6)
	NAAN	5339 (2.8, 2.2)	1908 (35.7, 35.9)	535 (10.0, 11.1)	406 (7.6, 7.6)	476 (8.9, 8.5)	895 (16.8, 14.9)	388 (7.3, 6.7)	349 (6.5, 7.8)	382 (7.2, 7.6)
Educational Attainment	<HS	10,229 (5.3, 9.6)	3841 (37.6, 29.6)	978 (9.6, 9.8)	690 (6.7, 7.9)	754 (7.4, 9.0)	1847 (18.1, 15.6)	683 (6.7, 8.1)	675 (6.6, 9.2)	761 (7.4, 10.8)
	≥HS	183,863 (94.7, 90.4)	59,147 (32.2, 32.5)	11,224 (6.1, 7.4)	7246 (3.9, 4.8)	4621 (2.5, 3.0)	53,255 (29.0, 24.2)	17,448 (9.5, 10.1)	18,403 (10.0, 11.1)	12,520 (6.8, 6.9)
Household Poverty Status	Not In Poverty	166,606 (85.8, 82.9)	51,380 (30.8, 31.5)	9162 (5.5, 6.7)	5199 (3.1, 3.8)	2580 (1.5, 1.9)	52,727 (31.6, 26.5)	16,856 (10.1, 10.9)	17,562 (10.5, 11.7)	11,140 (6.7, 7.0)
	In Poverty	27,487 (14.2, 17.1)	11,607 (42.2, 36.1)	3040 (11.1, 11.9)	2738 (10.0, 11.0)	2795 (10.2, 11.6)	2374 (8.6, 8.1)	1275 (4.6, 5.2)	1516 (5.5, 7.0)	2142 (7.8, 9.1)

NAAN: Native American or Alaska Native. HS: High School Completion. Note: ‘dep’ refers to N dependent children. All percentages are column-wise for total populations, and row-wise for EITC subgroups.

Table 4.3. National EITC Expenditures, Numbers Eligible for and EITC, Typical Credit Eligibilities, Numbers Lifted Out of Poverty, and FMD Prevalences Under Existing Policy and Policy Proposals, BRFSS 2019.

Outcome – Est, (95% CI) [IQR]	Existing Policy	Policy 1 (Expand State EITC)	Policy 2 (Generosity + 10%)	Policy 3 (Childless EITC)	Policy 4 (Marriage Penalty)	Policy 5 (No Phase-In)
EITC Expenditure in $ (billions) *	74.34 (72.73, 76.23)	78.89 (77.12, 80.97)	81.62 (79.85, 83.70)	83.11 (81.49, 84.98)	75.92 (74.32, 77.86)	82.91 (81.22, 84.86)
Federal EITC Only	68.03 (66.47, 69.75)	68.03 (66.47, 69.75)	74.83 (73.12, 76.73)	76.16 (74.57, 77.90)	69.49 (67.96, 71.27)	76.08 (74.44, 77.85)
State EITC Only	6.31 (6.13, 6.52)	10.86 (10.60, 11.17)	6.79 (6.59, 7.01)	6.96 (6.77, 7.16)	6.42 (6.23, 6.63)	6.83 (6.64, 7.04)
N Eligible for EITC (millions)	34.34 (33.79, 34.86)	34.34 (33.79, 34.86)	34.34 (33.79, 34.86)	41.00 (40.40, 41.62)	34.33 (33.79, 34.86)	34.34 (33.80, 34.87)
Federal EITC Only	32.60 (32.07, 33.14)	32.60 (32.07, 33.14)	32.60 (32.07, 33.14)	40.27 (39.68, 40.88)	32.60, 32.07, 33.13)	32.61 (32.08, 33.14)
State EITC Only	17.92 (17.59, 18.24)	32.81 (32.31, 33.34)	17.92 (17.59, 18.24)	20.95 (20.61, 21.32)	17.93 (17.59, 18.25)	17.94 (17.60, 18.26)
EITC Credit (Everyone) **	2474 [464, 4556]	2632 [494, 4694]	2717 [508, 5006]	1659 [803, 3947]	2538 [499, 4635]	2970 [534, 5289]
Federal EITC Only	2520 [500, 4237]	2520 [500, 4237]	2772 [550, 4660]	1465 [774, 3526]	2579 [528, 4425]	3026 [529, 5166]
State EITC Only	217 [94, 589]	289 [88, 603]	231 [99, 645]	223 [101, 501]	219 [96, 599]	236 [106, 638]
EITC Credit in $ (Already Elig.) ***	2474 [464, 4556]	2632 [494, 4694]	2717 [508, 5006]	2477 [1172, 4556]	2537 [498, 4635]	2971 [534, 5289]
Federal EITC Only	2520 [500, 4237]	2520 [500, 4237]	2772 [550, 4660]	2520 [1182, 4237]	2579 [528, 4425]	3026 [529, 5166]
State EITC Only	217 [94, 589]	217 [90, 529]	231 [99, 645]	272 [128, 600]	219 [96, 599]	237 [106, 639]
N Lifted Out of Poverty (millions)	3.49 (3.27, 3.73)	3.74 (3.50, 3.99)	3.87 (3.63, 4.12)	4.26 (4.01, 4.52)	3.55 (3.32, 3.79)	3.49 (3.28, 3.74)
Federal EITC Only	3.21 (2.99, 3.45)	3.21 (2.99, 3.45)	3.56 (3.33, 3.81)	3.92 (3.67, 4.18)	3.26 (3.04, 3.51)	3.21 (2.99, 3.45)
State EITC Only	0.23 (0.19, 0.30)	0.41 (0.33, 0.51)	0.26 (0.20, 0.32)	0.29 (0.23, 0.35)	0.24 (0.19, 0.31)	0.23 (0.19, 0.30)
FMD Prevalence (%)	15.2 (14.8, 15.6)	-	15.2 (14.9, 15.7)	15.5 (15.0, 16.0)	15.2 (14.7, 15.6)	15.3 (14.8, 15.7)
Among those likely eligible	22.8 (21.9, 23.9)	-	23.0 (22.1, 24.0)	23.7 (22.5, 24.8)	22.8 (21.8, 23.8)	23.1 (22.1, 24.2)

N: Number of people. EITC: Earned Income Tax Credit. CI: Confidence Interval. IQR: Inter-Quartile Range. * Assuming state-specific EITC participation rates under existing policy. ** Among those likely eligible for any EITC, a Federal EITC, or a State EITC (as appropriate). *** Among those likely eligible for any EITC, a Federal EITC, or a State EITC (as appropriate) under existing policy. Note: For space constraints, we present the point-estimated IQR of EITC credit eligibilities instead of 95% CI for a single point estimate. Across all policies, median total EITC credit 95% CI were at-most ±$108, Federal EITC credit 95% CI were at-most ±$52, and State EITC credit 95% CI were at-most ±$7. All FMD prevalence estimates under policy 2 were suppressed for high statistical uncertainty.

4.6 Relevant Appendices

Appendix 4.A. Additional Policy Scenario Details, BRFSS 2019.

In estimating EITC credit eligibilities under our alternate scenarios, there are a number of minor caveats relevant on a state-by-state basis. We discuss each below per policy proposal.

<u>All policies</u>

In estimating Federal and State EITC credit eligibilities under existing policy, we assume that any dependents are five years old for simplicity. While age did not affect EITC credit size federally, in DC, or in any state with a policy except Oregon in 2019, Oregon tax filers with dependents younger than three years old were entitled to a larger EITC. As this would add considerable complexity to our coding schema and affect a likely very small population, we do not incorporate this in our estimation of EITC credit eligibilities.

<u>Policy 3 (Expanding the "Childless" EITC)</u>

Several changes occurred under ARPA temporary expanding the "childless" Federal EITC for tax year 2021. These included increasing the credit phase-in rate from 7.65% to 15.3%, increasing the maximum plateau credit from $543 to $1,502, increasing the annual gross income at which the EITC begins to phase-out from $8,800 to $11,610 for single filers and from $14,820 to $17,550 for married filers, and increasing the phase-out rate from 7.65% to 15.3%. To make similar adjustments in 2019, we applied the same phase-in and phase-out rates as under ARPA, increased the maximum credit by 276.6% (mirroring the multiplicative change occurring under ARPA), increased the annual gross income at which the EITC begins to phase-out by 3.46% for single filers and by 5.31% for married filers (again, the same multiplicative changes as under ARPA).

In extending these changes to State EITC policies, we do the following:

- While otherwise following the Federal EITC, Iowa did not provide benefits to anyone without dependents whose income was above $15,500. We incorporate this restriction in our analysis by making Indiana follow the same ARPA-like structure until this maximum, then offering no credit above this maximum.
- Indiana uses the single-filer Federal EITC schedule for all filers. Therefore, we apply the ARPA-like structure for single filers for married filers in Indiana as well.
- The DC EITC uses the same maximum plateau credit as the Federal EITC for filers without dependents but sets its own wage at which the EITC begins to phase-out ($19,239) and its own phase-out rate (8.48%). Therefore, we incorporate the ARPA-like updated phase-in rate and maximum credit for single and married filers, but keep DC's existing maximum plateau credit wage and phase-out rate.
- The New York EITC lowers the credit individuals are eligible to based on concurrently received housing credits, which be as much as $75 for single filers and $150 for married filers. Due to tis, the effective EITC phase-out rate for New York is non-linear. However, as these benefits are generally small compared to the EITC and incorporating these changes would be complex, we do not incorporate housing credit reductions in our analysis for simplicity.
- Wisconsin did not provide EITC credits to filers without dependents. For this reason, we do not extend ARPA-like EITC credit changes to the Wisconsin State EITC.

Policy 4 (Extending the EITC plateau for married filers)

Census Bureau OPM thresholds vary based on total household size, and so set higher OPM thresholds for households with more than two adults or more than three children. To mirror the EITC banding structure, however, we apply the OPM threshold for two-adult households and where relevant three dependents.

In extending these changes to State EITC policies, we do the following:

- In many states, eligibility for any credit ends prior the relevant OPM threshold per household. Where this occurs, our proposal as-implemented effectively gets rid of the phase-out structure, providing the plateau credit to all those up until households become ineligible.
- Virginia set its own minimum wages filers must report in order for them to be eligible for any EITC credit, which varied based on the number of individual (counting adults and children) in the household. These were $12,490, $16,910, $21,330, $25,750, and $30,170 for one, two, three, four, and five-person households respectively. In some cases, these were actually higher than the new maximum plateau credit implied by the OPM. Therefore, we incorporated this restriction in determining EITC credit eligibilities for filers in Virginia.
- As discussed above, Iowa set its own maximum wage at which individuals are eligible for an EITC. We incorporated this restriction in determining EITC credit eligibilities for filers in Iowa.
- As discussed above, DC set some elements of its own EITC schedule for filers without dependents. We incorporated these in determining EITC credit eligibilities for filers in DC.
- As discussed above, Indiana use the Federal EITC for single filers for married filers as well. Therefore, we do not change EITC credit eligibilities for married filers in Indiana.

<u>Policy 5 (Eliminating the EITC Phase-In Structure)</u>

Where states set their own minimum earnings thresholds for individuals to be eligible for any credit, we incorporate these thresholds in determining State EITC credit eligibilities.

<u>NBER TAXSIM and UKCPR Discrepancies</u>

When comparing EITC characteristics reported by the UKCPR National Welfare Database and implied by the NBER TAXSIM 35 tax micro-simulator model, we identified the following discrepancies.

- DC provides the full Federal EITC for childless filers. As such, the adjustment factor implied by the UKCPR-NWD for those without dependents (40%) was incorrect.
- Maine matched 5% of the Federal EITC for all filers. As such, the adjustment factors implied by the UKCPR-NWD (12%) was incorrect.
- Wisconsin follows variable adjustment factors for filers with zero (0%), one (4%), two (11%), or three or more (34%) dependents. As such, the single adjustment factor implied by the UKCPR-NWS (4%) was only partially accurate.
- The NBER TAXSIM model applies minimum wage thresholds for EITC eligibility in Virgina equal to $7000 for single filers or $14,000 for married filers. No component of the Virginia tax code in 2019, to my knowledge, set EITC minimum wage thresholds as-such. Instead, the EITC appears to set minimum earnings thresholds as discussed above under 'Policy 4'. Virginia did offer a low-income tax credit to those with incomes below the Federal Poverty Level which individuals could instead of the EITC, and this may be the basis for the NBER TAXSIM thresholds. However, we chose to apply those stated in the Virgina tax code.

Appendix 4.B. Model Covariate Definitions, Sources, and Additional Details.

Level	Name	Description	Coding	Source
1	Age	In years	Continuous: Mean-centered	BRFSS
1	Sex	Interviewer-presumed	Binary: Male (=0), Female (=1)	BRFSS
1	Race	Self-classified	Categorical: White, Black, Asian, NAAN	BRFSS
1	Ethnicity	Self-classified	Binary: Non-Hispanic (=0), Hispanic (=1)	BRFSS
1	Educational Attainment	Self-reported	Binary: <HS (=0), ≥HS (=1)	BRFSS
1	Household Poverty Status	Based on state, imputed continuous income, and Official Poverty Measure	Binary: Not in poverty (=0), In poverty (=1)	BRFSS
1	Household Income	Imputed continuous annual income (presumed pre-transfers)	Continuous: B-Spline with 3 internal knots alongside other tax credit income.	BRFSS
1	Marital Status	Self-reported	Binary: Never married, unmarried couple, separated, widowed, divorced (=0), Married (=1)	BRFSS
1	Number of Dependents	Interviewer-coded	Categorical: None, One, Two, Three or more	BRFSS
1	Urban Residence	County-based	Binary: Rural (=0), Urban (=1)	BRFSS
1	Employment Status	Current	Binary: Unemployed or NILF (homemaker, student, retired, unable to work) (=0), Employed (for wages, self-employed) (=1)	BRFSS
1	Rental Status	Current	Binary: Own (=0), Rent or Other Arrangement (=1)	BRFSS
1	EITC Income	Expected total (Federal and State) EITC credit size eligibility under each scenario based on imputed continuous income	Continuous: B-Spline with 3 internal knots	BRFSS, NBER TAXSIM
1	Other Tax Credit Income	Expected total (Federal and State) non-EITC credit size	Continuous: B-Spline with 3 internal knots	BRFSS, NBER TAXSIM

		eligibility based on imputed continuous income, household composition, state of residence, and number of dependents.	alongside household income.	
2	Racial-Ethnic Composition of State Population	The proportion of state populations belonging to each racial-ethnic group.	Continuous by group: NH White, NH Black, NH Asian, NH NAAN, NH NHPI, NH Other, NH Multi-racial, Hispanic. Mean-centered, scaled, then incorporated into principal components for modelling.	ACS
2	Median Age of State Population	In years	Continuous: Mean-centered, scaled, then incorporated into principal components for modelling.	ACS
2	Educational Composition of State Population	The proportion of state populations 25 years and over by educational attainment	Continuous by group: <HS or GED, HS, Some College, College or More. Mean-centered, scaled, then incorporated into principal components for modelling.	ACS
2	Urbanicity of State Population[1]	The proportion of state populations residing in urban areas	Continuous: Mean-centered, scaled, then incorporated into principal components for modelling.	ACS, Decennial Census
2	Nativity of State Population	The proportion of state populations born outside the US.	Continuous: Mean-centered, scaled, then incorporated into principal components for modelling.	ACS
2	Occupational Composition of State Population[2]	The proportion of state populations 16 years and over working in blue-collar roles	Continuous: Mean-centered, scaled, then incorporated into principal components for modelling.	ACS, Hardy *et al.*,[282] Kouretsis & Bampouris[234]
2	Gross State Product (GSP) per Capita	In millions of chained 2017 dollars	Continuous: Mean-centered, scaled, then incorporated into principal components for modelling.	BEA

2	State Unemployment Rate	The average annual seasonally-adjusted proportion of the state labor force unemployed	Continuous: Mean-centered, scaled, then incorporated into principal components for modelling.	BLS
2	State Poverty Rate	The proportion of state families with incomes below the Official Poverty Measure (OPM) threshold for their household composition	Continuous: Mean-centered, scaled, then incorporated into principal components for modelling.	CPS-ASEC
2	State Population Uninsured	The proportion of the state population 19 to 64 years without health insurance coverage	Continuous: Mean-centered, scaled, then incorporated into principal components for modelling.	ACS
2	State Median Household Income	Over the preceding 12 months, in inflation-adjusted 2019 dollars	Continuous: Mean-centered, scaled, then incorporated into principal components for modelling.	ACS
2	State Minimum Wage	The absolute minimum hourly wage for non-farm employment	Continuous: Mean-centered, scaled, then incorporated into principal components for modelling.	DoL, UKCPR
2	State Medicaid Expansion	Whether states had expanded Medicaid coverage to those earning below 138% of the FPL by January 2019	Binary: No (=0), Yes (=1). Incorporated into principal components for modelling.	KFF[283]
2	State Maximum TANF and SNAP	The maximum combined monthly benefit from TANF and SNAP for a 3-person family	Continuous: Mean-centered, scaled, then incorporated into principal components for modelling.	UKCPR
2	State Government Political Control[3]	The number of executive (governorship) and legislative (house, senate) bodies under Democratic leadership	Continuous: Each body is scored as No (=0) or Yes (=1/3), for a total score of 0 (complete Republican leadership) to 1 (complete Democrat leadership). Incorporated into principal components for modelling.	UKCPR

BRFSS: Behavioral Risk Factor Surveillance System. NBER: National Bureau of Economic Research. ACS: American Community Survey. BEA: US Bureau of Economic Analysis. BLS: US Bureau of Labor Statistics. CPS-ASEC: Current Population Survey Annual Social and Economic Supplement. DoL: US Department of Labor. UKCPR: University of Kentucky Center for Poverty Research National Welfare Database. KFF: Kaiser Family Foundation. NAAN: Native American or Alaska Native. NHPI: Native Hawaiian or Pacific Islander. NH: Non-Hispanic. HS: High School. GED: General Education Diploma. NILF: Not in Labor Force. EITC: Earned Income Tax Credit. TANF: Temporary Assistance for Needy Families. SNAP: Supplemental Nutrition Assistance Program. GSP: Gross State Product. OPM: Official Poverty Measure. FPL: Federal Poverty Level. Note: All ACS figures relate to 2019 ACS 1-Year Estimates, except for county populations used in deriving state proportions living in urban areas, which are taken from the 5-Year 2017-2021 ACS. [1] ACS does not directly report state populations living in urban areas. Instead, we use county-level information from the 2020 decennial census on the proportion of county populations living in urban areas and county-level information from the 2019 ACS on total county populations to estimate the proportion of the total state population living in urban areas in 2019. [2] We follow the ILO's definition of blue-collar workers, classifying those employed in ISCO major group 6-9 occupations as blue-collar workers. As the ACS reports occupational populations classified according to SOC codes, we use Hardy *et al.*'s crosswalk of SOC and ISCO codes[282] (made available in R via the 'iscoCrosswalks' package developed by Kouretsis and Bampouris[234]) to identify all blue-collar occupations before summing these to calculate the total state adult population employed in blue-collar roles. [3] We use the state government political control index first reported by Klarner.[235] As the District of Columbia (DC) is a Federal district with limited governing power, we score each body for DC based on the 116th US Congress and US presidency. Nebraska, as the lone state with a unicameral system, has both legislative scores based on its senate composition.

Chapter 5.

Discussion.

5.1 Summarizing Findings

This body of research contributes to our understanding of how mental distress and social inequities in mental distress have changed over recent decades across the US (Chapter 2); how State EITC policies have shaped recent historical trends in these outcomes (Chapter 3); and how different kinds of EITC reform could affect population mental health, economic wellbeing, and social equity across the US if they were implemented in the future (Chapter 4). In Chapter 2 we documented substantial, near-universal increases in population mental distress over recent decades affecting young adults, those in poverty, and lower-SES non-Hispanic white women disproportionately. We also observed nuanced changes in mental health equity over time depending on the measurement scale and level of social granularity considered as well as the social groups focused on. In Chapter 3, however, we demonstrated that states which historically offered a refundable State EITC policy saw smaller increases in FMD prevalence over time and contemporaneously lower FMD prevalence overall. These differences were particularly large for women, those in poverty, and those likely eligible to receive a State EITC credit, as well as in states where refundable State EITC policies had been available for longer. We also found refundable State EITC availability was associated with steeper increases in mental distress over time for most racially minoritized groups and widening racial inequities in FMD for those non-Hispanic Black and NAAN, suggesting that the benefits of EITC policies as implemented are not universal. Finally in Chapter 4 we found that several EITC reforms would be expected to increase EITC availability, increase typical EITC credit amounts, or lessen poverty if they were implemented. While in most cases these reforms would disproportionately benefit socially disadvantaged groups, expanding the EITC for “childless” workers and addressing marriage penalties in the EITC would be expected to widen socioeconomic inequities through benefiting advantaged groups more. Unfortunately, we also found that none of the reforms we examined would be expected to substantively affect population mental distress or social inequities in mental distress.

While this research raises serious concerns over the direction of mental health and health equity trends in the US, it also suggests that state policymakers could mitigate against these concerns by implementing refundable State EITC policies, and that state and federal policymakers could lessen social economic inequities by reforming existing EITC policies. It likewise underscores the importance of structural policies and the political economy at large in shaping population mental health and health equity, as well as the importance of examining how the political economy mechanistically affects health inequity.

5.2 Implications for Future Research

Throughout this dissertation, we identify several important gaps in the existing literature, areas where existing evidence is insufficient, and methodologies that researchers should consider using more. First, our finding that mental distress and absolute social inequities in mental distress have significantly worsened over time supports the need for more retrospective studies examining the impact of recent political economy shifts on health and health equity. For example, while this dissertation focuses on EITC policies as a form of government income assistance, market-based economic changes such as declining worker bargaining power[284,285] and increasing corporate market power[286,287] could also explain our observed trends in Chapter 1; especially given both have contributed to rising income inequality[288,289] which is known to widen health inequities.[30] This kind of research would also address recent calls to more substantively examine the corporate determinants of health and health equity.[290,291] Non-economic political economy shifts such as criminal disenfranchisement[292] and the relaxation of campaign finance laws following *Citizens United v. Federal Election Commission*[293] will also be important to study in the context of health inequity trends. For example, while Beckfield and Krieger show political incorporation of subordinated social groups tends to lessen health inequities over time,[294] we have seen the opposite occur. Black and Latinx populations have been disproportionately disenfranchised over recent decades[292] and campaign donations from large donors, which primarily benefit male and white candidates,[295] have increased as a share of all donations over time.[296]

Although understanding how the political economy shapes health and health equity does not itself bring about change, I believe it is essential that we in epidemiology prioritize examining the political economy of health in our work now for several reasons. First, Americans overwhelmingly agree that our political and economic systems need reform, and a majority believe that democracy itself is not working.[297] This is actively contributing to rising cultural populism, the embrace of far-right political ideologies and authoritarian modes of government, and the re-election of President Trump;[298] all of which research and prior experience suggests are or will be detrimental to health and health equity.[299,300] In this context, it is essential that we in epidemiology demonstrate the expected negative health and health equity impacts of these political economy changes, identify an alternative set of political and economic reforms which those who feel left behind can embrace, and advocate for those reforms through policy-relevant research. If we do not, we risk failing to proactively address some of the largest health determinants of coming decades such as climate change, economic inequality, the healthcare and social assistance needs of our ageing population, and the emergence of novel infectious diseases.

Separately, this dissertation supports the need for more causally robust, cohort-based studies examining the immediate and long-term impacts of EITC recipiency on mental health and health equity. While there is a strong theoretical basis for believing EITC receipt improves mental health (e.g., through reducing immediate financial hardship,[37] raising educational attainment in childhood[301] and incentivizing employment in adulthood[37]), the existing literature has reached mixed conclusions on whether Federal and/or State EITC policies improve mental health. This literature has also mostly been based on quasi-experimental designs or used methods that are not sufficient for causal interpretations. This recommendation is supported by our observations in

Chapter 3 that the contemporaneous association between State EITC availability and FMD prevalence was small and inconsistent over time and in Chapter 4 that no EITC reform examined would be expected to substantively affect FMD prevalence. As one example of how this recommendation could be implemented, researchers could partner with the Census Bureau to link individuals and families included in various longitudinal cohort studies (e.g., the Health and Retirement Study or Panel Study of Income Dynamics) to their prior decennial census and individual tax return information using their protected identification key,[302] then use this in combination with a robust causal approach such as g-computation[303] to assess the short- and long-term impacts of EITC receipt on several health outcomes. This would address the main limitations of our dissertation (i.e., the lack of individual follow-up, uncertain measure of EITC recipiency, non-specific mental health measure, and non-causal designs in Chapters 3 and 4), as well as the main limitations of existing research.

Finally, our analysis in Chapter 4 demonstrates that simulation modelling is an effective way to prospectively assess how different policy reforms could impact health and health equity if implemented. As policymakers are increasingly encouraged to adopt a “Health in All Policy” mindset and consider the health implications of policy reform,[304–306] our findings suggest that simulation modelling could be useful in accomplishing this goal. However, in reviewing the literature it appears this technique has not been used extensively in the context of political economy research. For example, to our knowledge our analysis in Chapter 4 was the first to simulate how different potential EITC reforms could impact health and health equity if implemented. This kind of analysis could be especially useful to health researchers looking to improve upon existing social policies or understand how novel policies without an existing evidence base could impact health (e.g., as we use them in modeling the health impact of removing the EITC phase-in structure entirely). As simulation methods have already proven useful in other areas of policymaking (e.g., in modelling the potential health impacts of social distancing policies during the COVID-19 pandemic[307] and policies preventing greenhouse gas emissions[308]), they would likely also be useful in examining how changes to the political economy could impact health equity as well.

5.3 Implications for Future Policy

Our findings have several implications for future policy prioritization and development. Starting with Chapter 2, our observation that population mental distress and social inequities in mental distress have worsened over recent decades suggests that policymakers should consider implementing policies geared towards addressing these trends. This could include expanding health insurance coverage,[142] improving access to affordable childcare[143] and housing,[144] and expanding social assistance policies such as child tax credits[145] and EITCs.[309] As adolescents[46,310] and young adults (Chapter 2) have seen the sharpest increases in mental distress over time, it is especially important that any policy response be geared towards their needs and concerns. According to The Lancet Psychiatry Commission on Youth Mental Health, much of this decline can be attributed to children and young adults' concerns over the political, economic, social, and environmental landscape of their future.[310] This is understandable for several reasons. They are more likely to be affected by the worst consequences of climate change, are expected to be worse off economically than their parents[311] and to be burdened with supporting an ageing population,[312] are more likely to view rising economic inequality as a serious issue,[313] and are increasingly disillusioned with the ability of democratic policymakers to address these crises.[314] They are also more aware of these macro-trends due to unregulated social media[310] which, while democratizing access to information, can negatively affect mental health via their recommendation algorithms promoting polarizing content, fake news, and hate speech.[315] Taken together, this would suggest that systemic policy change – including social media regulation – is needed to address the youth mental health crisis.

Although our analysis in Chapter 3 was not causal, its findings suggest that State EITC policies may be modestly effective at reducing population mental distress and improving sex- and poverty-based inequities in mental distress over time. This would broadly support policymakers expanding the availability of State EITC policies nationwide if their goal was to improve mental health and health equity. As State EITC availability was not associated with improvements for racially minoritized groups, however, our findings suggest that some aspect of EITC availability, uptake, and/or scheduling has not met the needs of these groups. While this is likely related in part to racial differences in tax filing and EITC uptake,[203,204] research by Linos *et al.* finds that neither are improved by EITC awareness messaging alone.[316] Instead, policymakers must identify ways to reduce the administrative burden associated with tax filing and claiming an EITC.

Our analyses in Chapter 3 also suggest State EITC policies may be effective in lowering FMD prevalence contemporaneously, though these findings were inconsistent and somewhat contradicted in Chapter 4 where we found no EITC reform examined would be expected to lower FMD prevalence or narrow social inequities in mental distress individually. This discrepancy could be explained if EITC policies primarily improve mental health through reducing individual susceptibility to disease over longer periods (e.g., by preventing adverse childhood events,[317] raising educational attainment,[301] or increasing employment[37]) as opposed to through reducing immediate financial hardship. If this were the case our results would still support EITC policies as long-term tools for improving population mental health, though suggest other policies or policy reforms are needed to improve population mental health immediately.

To that end, our analyses in Chapter 4 suggest several EITC reforms could reduce financial hardship and improve social inequities in income. Based on these findings, we would recommend that state policymakers looking to address each outcome consider implementing a refundable State EITC policy if none currently exists and making existing policies refundable if they are not. We would also recommend that federal and/or state policymakers consider re-introducing similar

EITC changes as under ARPA for “childless” adults; shortening or eliminating the EITC credit phase-in period; and raising the absolute generosity of EITC policies. However, it is also important that policymakers look to shield against any negative impacts of EITC expansions. For example, while EITC policies benefit recipients economically, they also tend to lower wage growth for low-income workers as a whole through increasing labor supply which allows hiring firms to offer lower wages.[260,261] This could partly be addressed through concurrently raising the minimum wage as others have proposed.[246,262] Likewise, as we and others have found expanding the “childless” EITC would worsen social inequities in income,[250] other policy changes may be needed to ensure EITC policies remain equitable. For example, removing the requirement that all household members applying for an EITC have a Social Security number (SSN) would disproportionately benefit Latinx and Black families, and has been advocated for in the past.[318,319] Finally, our results demonstrate that population mental health, economic wellbeing, and social inequities in each can be significantly improved through independent state policy change. This finding is especially relevant to state policymakers given the incoming Trump administration has historically cut social assistance programs.[320]

6. References

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