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State minimum wage and mental health in the United States: 2011-2019

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ABSTRACT

Consistent with a rise in "deaths of despair" (drug overdose, alcoholism, and suicide), the percentage of Americans reporting major mental and emotional problems in all 30 of the last 30 days has been increasing. Based on the hypothesis that this rise in extreme levels of distress is driven partly by financial hardships, this study investigates whether higher state minimum wages reduce the likelihood of extreme levels of distress among low-income, prime-age Americans with no postsecondary education. By matching state minimum wages with individual-level data from the 2011–2019 Behavioral Risk Factor Surveillance System, this study finds that a ten percent increase in the minimum wage is associated with a 0.4–0.5 percentage-point decline in the likelihood of extreme distress. The finding is consistent with the notion that growing extreme distress is attributable to despair driven by economic hardships and financial strain.

1. Introduction

A recent study by Blanchflower and Oswald (2020) documented the proportion of Americans reporting extreme levels of mental distress (the percentage who reported major mental and emotional problems in all 30 of the last 30 days; "extreme distress" hereafter) increased from 3.6 percent in 1993 to 6.4 percent in 2019. The authors reported two important findings: (1) the increase was larger among working-class, middle-aged people, and (2) the decline in the share of manufacturing jobs at the state level explained a great deal of the increase in extreme distress, pointing to the role of poor labor market prospects. Their finding is consistent with "deaths of despair" (drug overdose, alcoholism, and suicide) that have been rising in the past two decades, as documented by Case and Deaton (2015). The important question for researchers and policymakers is whether economic policies can alleviate the rise in extreme mental distress.

Recently, the minimum wage has been gaining attention among researchers as a policy tool to improve various health outcomes (see Leigh et al., 2019 for a review). Three recent papers that examine the link between minimum wages and suicide, which is closely associated with mental health, all find that higher minimum wages are associated with lower suicide among less-educated individuals in the United States, suggesting that economic policies could reduce financial despair (Dow et al., 2020; Gertner et al., 2019; Kaufman et al., 2020). This study contributes to the literature by examining whether higher state minimum wages are associated with mental health among low-income, less-educated prime-age workers in the United States.

Although it is plausible that increases in the minimum wage could improve minimum-wage workers' mental health by alleviating financial stress, there has been surprisingly little research on the effect of minimum wages on mental health. The findings outside the United States seem mixed. Reeves et al. (2017) and Kronenberg et al. (2017) use a differences-in-differences design to study the effect of a 1999 increase in the minimum wage on mental health of workers in the United Kingdom and come to different conclusions even though they exploit the same natural experiment and use the same data (the British Household Panel Survey), presumably due to their different definitions of treatment and control groups.

Horn et al. (2017) and Narain and Zimmerman (2019) both examine workers in the United States and find a positive effect of minimum wage increases on mental health among women without a college degree by using the Behavioral Risk Factor Surveillance System Survey (BRFSS henceforth) from 1993 to 2014. Kuroki's (2017) study that uses the BRFSS 2005–2010 and finds a positive association between higher state minimum wages and life satisfaction among workers without a college degree in the United States is also in the same spirit. While Narain and Zimmerman (2019) do not provide readily interpretable results, as their independent variable is adjusted minimum wages (the product of the ratio of the 1-year lagged minimum wage to the state median wage and the national median wage), the magnitude of the estimate found in Horn et al. (2017) is extremely small; a ten percent increase in the minimum wage is associated with 0.07 fewer bad mental health days in the past 30 days, or a 1.55% reduction relative to the sample mean (4.35 bad mental health days). Taken literally, doubling the minimum wage (a 100%

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increase, which is almost equivalent to increasing it from $7.25 to $15) would not reduce even one bad mental health day in a month. However, their findings may be underestimated because they seem to include individuals whose household income is above a certain threshold. This inclusion is likely to underestimate the income-induced mental health effect of a minimum wage hike, as the effect of the minimum wage is likely to be greater at the bottom of the income distribution.

Moreover, Horn et al. (2017) do not control for respondents' health insurance status, though this information is available in the BRFSS. While it might be reasonable to assume that most minimum-wage workers do not have employer-provided health insurance, many of them have Medicaid. Especially since 2014, many states have expanded Medicaid to low-income childless adults under the Affordable Care Act (ACA). Evidence suggests that having health insurance gives people more access to mental health professionals (Finkelstein et al., 2012), and Medicaid expansions under the ACA also increased use of mental health treatment among the newly enrolled (Mulvaney-Day et al., 2019). Though the relationship between minimum wages and health insurance is ambiguous (higher minimum wages allow some previously uninsured workers to purchase health insurance but make Medicaid recipients ineligible for Medicaid and become uninsured), controlling for respondents' health insurance as well states' Medicaid expansion status may be important in estimating the mental health effect of the minimum wage. A recent study also finds that higher minimum wages may increase health insurance coverage among low-income households (Kuroki, 2021). For these reasons, this study makes several changes to Horn et al. (2017) and reexamines the mental health effect of minimum wages with more recent data.

To examine the effect of minimum wages on mental health among low-income, less-educated prime-age workers, this study first uses event study models to test for parallel pre-trends and capture the time path of effects around the time of minimum wage increases. Then, using the standard approach in the minimum wage literature, difference-in-differences models that leverage panel variation in state minimum wages over time are estimated. The results from difference-in-differences models suggest that a ten percent increase in the minimum wage is associated with a 0.4–0.5 percentage-point decline in the likelihood of extreme distress. However, the minimum wage is negatively associated with the number of bad mental health days only among men. The event study model supports parallel pre-trends, and the placebo regressions indicate that higher minimum wages do not affect mental health among low-income workers with postsecondary education. The finding is consistent with the notion that growing extreme distress is attributable to despair driven by economic hardships.

2. Data and methodology

The main data set used is the 2011–2019 BRFSS, which is a household-level survey collected by the U.S. Government's National Center for Chronic Disease Prevention and Health and the largest continuously conducted health survey system in the world. The most recent wave, the 2019 BRFSS, includes some information for 2020 (January–April), but respondents from 2020 are excluded as the number of observations from 2020 is small (less than 0.4% of the sample). The hypothesis that higher minimum wages improve mental health by raising earnings at the low end of the income distribution cannot be tested directly because the BRFSS asks about respondents' household income, not hourly wages. Thus, the major challenge is identifying those who are most likely to be affected by minimum wage legislation. Following the literature, the sample is restricted to employees who do not have any college education (i.e. high school dropouts and high school graduates). Unemployed people are not included, but the literature suggests that the disemployment effect of minimum wages is rather small (Cengiz et al., 2019).

Importantly, single-adult households that report annual household incomes above $20,000 are excluded from the analysis. If the number of adults in the household is greater than one, $50,000 is chosen as the cutoff. The BRFSS provides information on household income as a categorical variable, and the next income category is "$50,000-$75,000", which would include many people who earned more than the median household income (which range from $50,000 to $69,000 during the period 2011–2019, according to the U.S. Census Bureau (2020)) and thus were less likely to be affected by minimum wage legislation. This sample restriction based on household income is the main difference from Horn et al. (2017). The sample is further restricted to those between 25 and 54 years old—prime-age workers—who for the most part have finished their formal schooling and are not on the verge of retirement. Respondents who refused or were unsure of their response, or whose response is missing, for any of the variables included in the analyses are also excluded. Fig. A1 in the appendix shows how many respondents are excluded at each step during sample construction.

Reasonable observers may rightly point out that households that earn these levels of income may not contain minimum wage workers, as the federal minimum wage of $7.25 only results in approximately $15,000 a year for a full-time worker. However, three factors need to be considered. First, there is some evidence that higher minimum wages lead to higher wages for workers who earn wages slightly above the minimum wage. If the lowest-paid employees are paid more due to higher minimum wages, other workers change their expectation of "fair" wages and feel that their wages also need to be raised (Falk et al., 2006). This in turn encourages employers to raise the wages of those employees who use the minimum wage as a benchmark to maintain morale and productivity. Autor et al. (2016) document this spillover effect of higher minimum wages on the wages of workers earning above the minimum wage. Clemens et al. (2018) also find some evidence on the spillover effect on workers who earn higher wages. Second, among households with more than one adult, many minimum wage workers are not breadwinners of low-income families but people with spouses who are paid more than the minimum wage (Shannon, 2013). Third, many states have minimum wages above the federal level of $7.25.

This study examines two outcome variables: "the number of bad mental health days" and "extreme distress". Bad mental health days is respondents' answer to the BRFSS 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?*" Extreme distress is defined as the probability of reporting that one's mental health was not good every single day in the past 30 days and measured as those who gave the answer 30 to the question above. This measure of mental health was recently proposed and used by Blanchflower and Oswald (2020). The use of the extreme distress measure is another major difference from Horn et al. (2017).

People who were surveyed in a particular state and year are matched with the data on minimum wages obtained from the U.S. Department of Labor's (2021) *Changes in Basic Minimum Wages in Non-Farm Employment Under State Law*. Wage rates are for January 1 of each year. During the sample period, there was no increase in the federal minimum wage ($7.25), but there were 143 state-level minimum wage hikes during the period. Table A1 in the appendix summarizes these changes. Since there are states with no minimum wage law (Alabama, Louisiana, Mississippi, South Carolina, and Tennessee) and states with minimum wages below $7.25 (Georgia and Wyoming), the effective minimum wage is defined as the higher of the state and federal minimum wage in each state. The nominal minimum effective wage is converted to January 2021 dollars using the Consumer Price Index obtained from the Federal Reserve Bank of St. Louis (2021). In this study, city or county minimum wages are not considered, as the BRFSS does not ask about the city or county of residence.

To estimate the effect of minimum wages on mental health, this study uses ordinary least squares (OLS) for bad mental health days and linear probability models for extreme mental distress. The conventional state and time fixed effects regression specification is as follows:

$$MentalHealth_{it} = \beta ln(MinimumWage_{st}) + \alpha_{1s}State_s + \alpha_{2t}Time_t + \gamma X_{it} + \rho W_{st} + \varepsilon_{it} \quad (1)$$

where i indexes individuals, s indexes states, and t indexes year. The dependent variable $MentalHealth_{it}$ is the number of bad mental health days or a binary measure of extreme mental distress (coded as 1 for those who reported 30 bad days out of 30, and zero otherwise). Here, *State* and *Time* are state and year dummies, and ε_{it} is the regression error term. The variable $MinimumWage_{st}$ describes variation in state-level minimum wage policies, and the coefficient of interest, β, is a difference-in-differences estimator of the effect of changes in the minimum wages on mental health.

X_{it} represents a set of socioeconomic characteristics. Personal characteristic variables, which are all binary, are respondents' race and ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, and other), age group (25–29, 30–34, 35–39, 40–44, 45–49, and 50–54), educational attainment (high school dropout and high school graduate), marital status (married, divorced, separated, widowed, cohabitating, never married), and whether the respondent has a child or children. Importantly, whether the respondent has health insurance is included to control for access to healthcare. Month of interview dummies are also included to control for seasonality in mental health (Christodoulou et al., 2012). Regressions do not include state-specific time trends, as an increasing number of researchers caution against using unit-specific time trends (e.g. Meer & West, 2016). Indeed, Borusyak and Jaravel (2017) state that "[they] do not recommend including unit-specific time trends in any difference-in-differences or event study specifications" (p.17).

Finally, as the BRFSS started cell phone interviews beginning in the 2011 survey, a "cell phone" dummy, interacted with year, is included in all regressions. Not surprisingly, the proportion of interviews conducted with respondents with lower incomes, with lower educational levels, or who were in younger age groups increased as these groups are less likely to own a landline phone. Their characteristics suggest that cell phone respondents are also more likely to be minimum-wage workers. As Blanchflower and Oswald (2020) report that the incidence of extreme distress is higher among cell phone users, the type of interviews may be correlated with both minimum wages and mental health.

To control for time-varying state-level economic conditions (W_{st}), poverty rate and unemployment rate) are included in the regressions. State-level data on poverty rates are obtained from the U.S. Census Bureau (2021a) *Small Area Income and Poverty Estimates (SAIPE) Program*. State-level annual unemployment rates are obtained from the U.S. Bureau of Labor Statistics' (2020) *Statewide Data, Annual Average Series*. To control for state-level anti-poverty policies, the following covariates are obtained from the University of Kentucky Center for Poverty Research (2021): the maximum Temporary Assistance for Needy Families (TANF) benefit for a family of four, the maximum Supplemental Nutrition Assistance Program (SNAP) benefit for a family of four, the state Earned Income Tax Credit (EITC) as a percentage of the federal EITC, and population share receiving SSI. State population is obtained from the U.S. Census Bureau (2021b). Finally, an indicator variable for post Affordable Care Act Medicaid expansion is included. Note that the variable is adjusted to take into account the pre-expansion period. For example, Michigan expanded Medicaid in April 2014, and thus the variable for Michigan equals 9/12 = 0.75 for 2014 and one from 2015 to 2019. Information on the ACA Medicaid expansions comes from the Kaiser Family Foundation (2021).

A concern with the difference-in-differences model above is that mental health in states that did and did not increase minimum wages might not have followed similar trends. The parallel trends assumption—i.e. conditional on the control variables included in the model, mental health would have followed similar trends across states if not for differential changes in their minimum wage policy—would be violated if there was some time-varying confounder that changed differentially across the states. To increase the likelihood that the parallel trends assumption holds, this study augments the difference-in-difference model with two additional models: event study models and placebo regressions.

As a generalized extension of difference-in-differences models, event study models allow for dynamic lags and leads to the event of interest to be estimated. Specifically, the main purpose of the event study model is to check for pre-trends, i.e. the possibility that the trends in mental health to trend upward or downward in the time leading up to events. The standard event study model would have one event per state with a set of mutually exclusive dummy variables, each equal to one when an event was a certain number of periods away (e.g. Medicaid expansions). However, in the case of minimum wage hikes, there are two methodological issues: (1) minimum wage policies typically vary in magnitude, and (2) multiple minimum wage increases often occur in the same state in quick succession. There is no clear consensus on how to conduct an event study when events occur multiple times per unit and their treatment intensity differs both across individuals and across events.

This study adopts the strategy shown in Schmidheiny and Siegloch (2019). First, the intensity of minimum wage hikes is used instead of dummy variables. For example, if a minimum wage hike was $0.50, the event study variable for "two periods before an event" would be equal to 0.5 two periods before the event, and zero other times. Also, as there are multiple events per state, if a given state in a given year was, for example, both two years after a minimum wage hike and one year before another minimum wage hike, both relevant event variables are the exact size of a change in the minimum wage. Second, the endpoints are "binned" to implicitly assume that the effect builds up to the endpoint and stays constant thereafter, as event study models without binned endpoints implicitly assume that treatment effects drop to zero outside of the effect window. The number of leads and lags is chosen to be 3 years before and after each change in the minimum wage. To construct lags and leads with as much information as possible, minimum wage hikes occurring between 2009 and 2021 are utilized. As an illustration, Table A2 in the appendix shows how event study variables for endpoints are binned using two states: Oregon, which had many minimum wage changes, and Texas, which only had the federal minimum wage changes. The event study regression takes the following form:

$$MentalHealth_{it} = \sum_{k=-3,\, k\neq -1}^{3} \beta^k d_{st}^k + \alpha_{1s}State_s + \alpha_{2t}Time_t + \gamma X_{it} + \rho W_{st} + \varepsilon_{it} \quad (2)$$

where

$$d_{st}^k = \sum_{k=-\infty}^{-3} \Delta MinimumWage_{s,\,t-k} \; if \; k = -3$$

$$d_{st}^k = \Delta MinimumWage_{s,t-k} \; if -3 < k < 3$$

$$d_{st}^{k} = \sum_{k=3}^{\infty} \Delta MinimumWage_{s,\ t-k} \quad if\ k = 3$$

where $\Delta MinimumWage_{st} = MinimumWage_{st}$ - $MinimumWage_{s,\ t-1}$. Treatment variables d_{st}^{k} are binned at the endpoints [-3, 3]. The basic idea of binned event study variables at the endpoints is that the maximum lag (lead) takes into account observable past (future) events going beyond the effect window.

As it is conventional, $k = -1$ is omitted as the reference period to normalize β^{-1} to zero, and treatment effects β^{k} are therefore expressed relative to one year prior to the event. Event leads allow for the inspection of parallel trends before minimum wage hikes. Unbiased estimation of treatment effects depends on the assumption that, in the absence of minimum wage hikes, treated and control states would have maintained similar differences as in the baseline period ($k = -1$). Therefore, if parallel pre-trends hold, the estimated coefficient should be statistically indistinguishable from zero for periods $k = -3$ and $k = -2$. If there is an immediate effect of minimum wage hikes, the estimated coefficients should shift discontinuously at the time of the hikes ($k = 0$). Event lags reveal whether treatment effects are temporary or dynamic. Positive coefficients for periods $k > 0$ would suggest the dynamic effect of minimum wage hikes.

The "placebo" sample consists of low-income workers who have at least some college education. Because workers with postsecondary education are unlikely to work minimum wage jobs, minimum wage hikes are less likely to affect those workers with higher education levels. If there was a distinct shock to or secular trend among low-income workers in high-minimum wage states over this period, the effects of these shocks should show up in mental health among the placebo regressions as wells. If the placebo models fail to find significant effects of minimum wages, then it is unlikely that unobservable factors are driving the results for less-educated workers in the difference-in-difference regressions.

In this study, following Horn et al. (2017) and Dow et al. (2020), models are estimated separately for men and women, as they differ in both labor market participation rates and the likelihood of psychological distress (Blanchflower & Oswald, 2008). While the share of minimum wage workers has been declining for both men and women during the sample period, the share is always larger among women than among men. In 2011, 6 percent of women who were paid hourly rates had wages at or below the federal minimum wage, compared with 4 percent of men (U.S. Bureau of Labor Statistics, 2011). In 2019, the numbers shrank to 3 percent and 1 percent, respectively (U.S. Bureau of Labor Statistics, 2019).

Table 1 shows summary statistics for each gender and education group and reveals that 4.8 percent of low-income less educated men and 7.7 percent of women interviewed in the BRFSS reported extreme distress, while 4.4 percent and 6.6 percent, respectively, of their more educated counterparts did. On average, low-income, less-educated men and women have 3.3 and 5.0 bad mental health days, respectively, while their more educated counterparts have 3.5 and 5.0 days. It is interesting to note that less-educated workers are more likely to report extreme distress, which is the likelihood of reporting major mental and emotional problems in all 30 of the last 30 days, though the average bad health days are not very different between these two groups, which suggests that the minimum wage may affect these measures of mental health differently. In terms of socioeconomic characteristics, less-educated workers in the sample are more likely to be non-Whites, old, and uninsured.

As is standard in the minimum wage literature, standard errors are clustered at the state level. Both ordinary least squares (OLS) and weighted least squares (WLS), which use BRFSS-provided sample weights, are used in difference-in-difference regressions below. As shown below, unweighted results and weighted results are different for both genders, but especially for men. While it is common to use weighted regressions, more and more researchers are cautious about applying weights in their estimations (e.g. Croezen et al., 2015). Use of the sample weight is necessary to make generalizations from the sample to the population when (1) the purpose of a study is to estimate descriptive statistics of interest for a population, and (2) certain groups in the sample overrepresent or underrepresent the US population. However, if the purpose is estimating causal effects, and if the sampling probabilities vary based on explanatory variables, controlling for these variables may make weighting unnecessary for consistency, and weighting may be

Table 1
Summary statistics.

	Low-income, no college education, age 25-54		Low-income, college graduate or some college education, age 25-54	
Variables	Men (n = 45,271)	Women (n = 46,932)	Men (n = 36,287)	Women (n = 61,046)
Personal characteristics:				
Extreme Distress	0.048	0.077	0.044	0.066
Bad mental health days	3.3	5.0	3.5	5.0
High school dropout	0.292	0.225	0	0
High school graduate	0.708	0.775	0	0
Some college	0	0	0.591	0.594
College	0	0	0.409	0.406
White	0.503	0.535	0.658	0.648
Black	0.100	0.154	0.101	0.148
Hispanic	0.315	0.236	0.126	0.108
Other	0.083	0.076	0.115	0.097
Age 25–29	0.163	0.121	0.233	0.178
Age 30–34	0.166	0.140	0.190	0.161
Age 35–39	0.156	0.145	0.156	0.151
Age 40–44	0.154	0.157	0.134	0.153
Age 45–49	0.170	0.191	0.136	0.163
Age 50–54	0.192	0.246	0.150	0.193
Married	0.530	0.446	0.529	0.461
Divorced	0.102	0.171	0.092	0.175
Widowed	0.008	0.027	0.006	0.020
Separated	0.036	0.069	0.019	0.039
Never married	0.229	0.227	0.285	0.242
Cohabitating	0.095	0.061	0.069	0.063
Have children	0.558	0.611	0.501	0.577
Health insurance	0.656	0.725	0.812	0.844
State characteristics:				
Real minimum wage	9.0	8.9	9.0	8.9
State poverty	13.5	13.8	13.2	13.5
State unemployment	5.3	5.5	5.1	5.4
Medicaid expansion	0.45	0.413	0.457	0.421
TANF benefit, family of four	586	574	590	575
SNAP benefit, family of four	730	736	732	734
State EITC as a percentage of the federal EITC	0.108	0.098	0.103	0.096
Population share receiving SSI	0.024	0.024	0.023	0.024
Population	8,873,201	8,190,493	7,714,254	7,264,144

Notes: Table shows unweighted means for each group, covering the years 2011–2019. Observations with missing demographics are excluded from the analysis sample. All personal characteristics except for bad mental health days are binary variables.

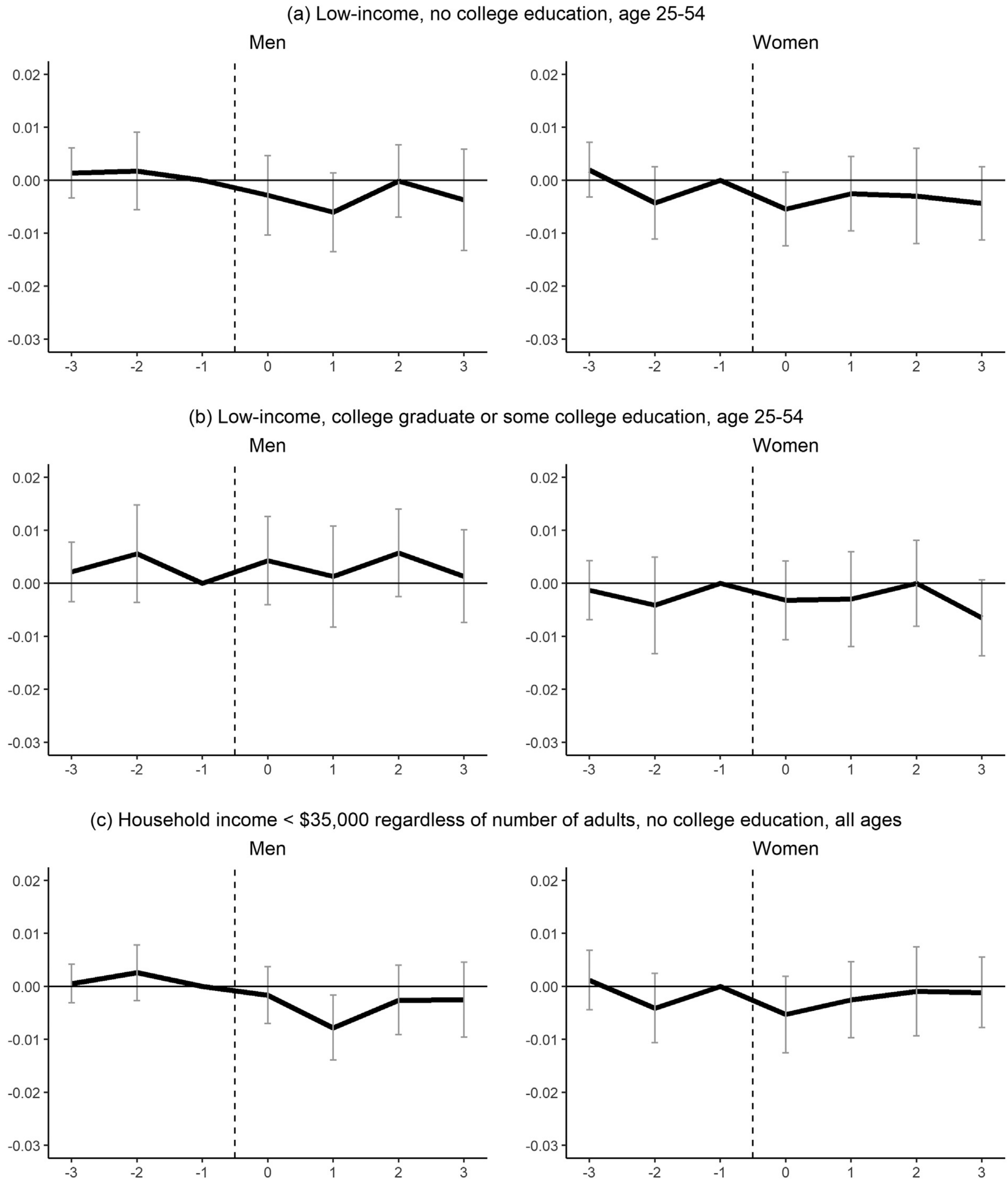

Fig. 1. Event study models: Extreme distress, Notes: The figures plot estimated event time coefficients together with 95 percent confidence intervals. Standard errors are clustered at the state level. The regressions include control for individual characteristics and state characteristics shown in Table 1, as well as month fixed effects, state fixed effects, year fixed effects, and cellphone-year interactions. The parameters are normalized so that the coefficient equals zero at −1 on the horizontal axis.

harmful for precision (Solon et al., 2015). Thus, unweighted results are emphasized in this study.

3. Results

3.1. Event study

Panel (a) of Fig. 1 illustrates the coefficients (and 95 percent confidence intervals) from the event study model for extreme distress by gender among low-income workers with no postsecondary education. Recall that the parameters are normalized so that the coefficient equals zero one year before the policy went into effect—that is, at −1 on the horizontal axis. If the parallel trends assumption holds, then we would expect that the estimated coefficients at −3 and −2 on the horizontal axis would be close to zero, and indeed this is the case for both men and women. Point estimates are not significantly different from zero for men

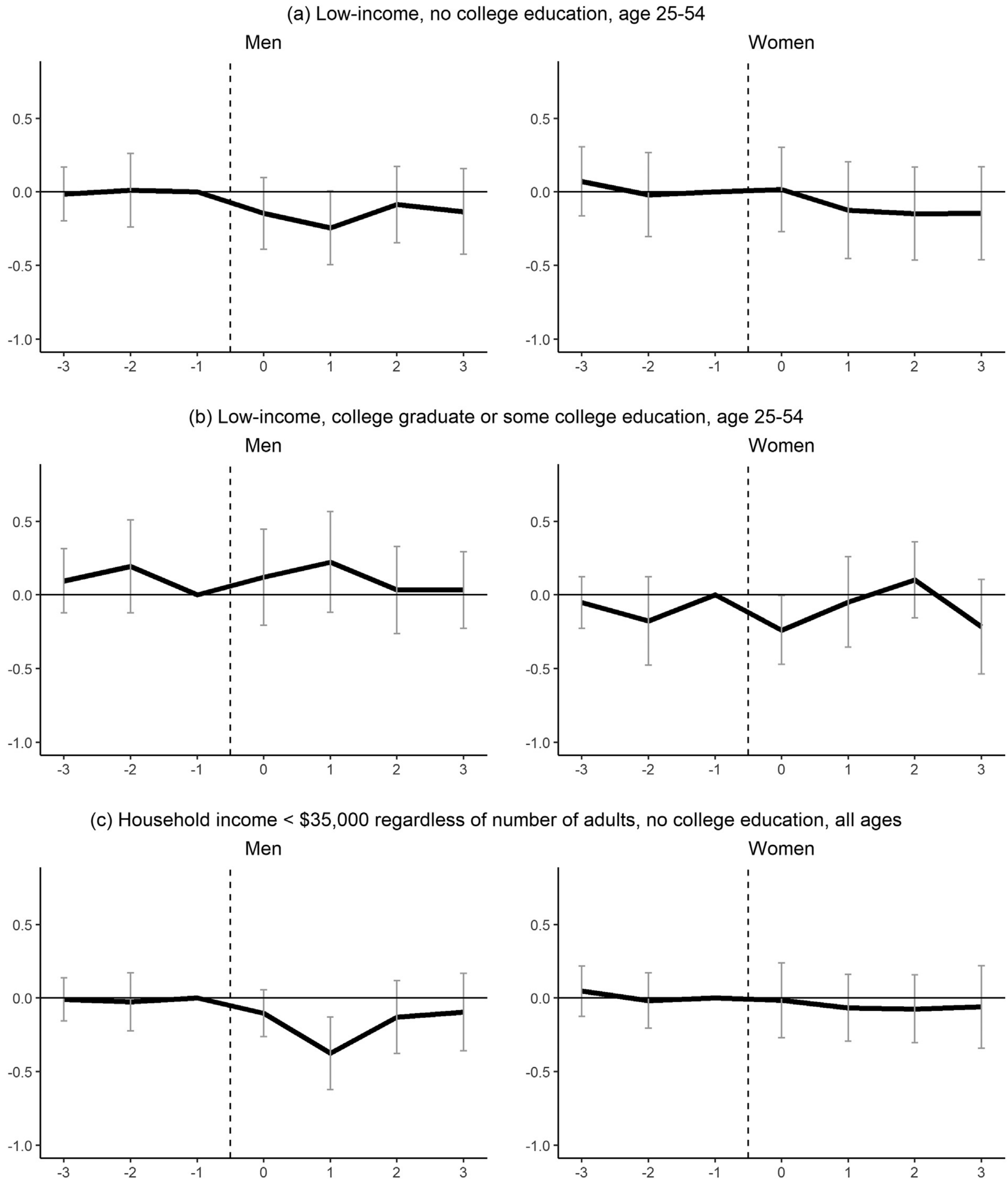

Fig. 2. Event study models: Bad mental health days.
Notes: The figure shows coefficient estimates from the event study together with 95 percent confidence intervals. Standard errors are clustered at the state level. The regressions include control for individual characteristics and state characteristics shown in Table 1, as well as month fixed effects, state fixed effects, year fixed effects, and cellphone-year interactions. The parameters are normalized so that the coefficient equals zero at −1 on the horizontal axis.

and women for the years leading up to a minimum wage increase. This supports parallel pre-trends—workers in states that increased their minimum wages did not experience differential trends in mental health in the years leading up to the implementation of the higher minimum wage. At time 0, the estimated event time coefficients exhibit a discontinuous downward shift for both genders and for both mental health measures, though the decline is statistically indistinguishable from zero. The coefficients on the lagged effects of the minimum wage are also statistically insignificant, though they consistently have a negative sign for both men and women.

Panel (b) of Fig. 1 shows the coefficients from the event study model for extreme distress for the placebo sample of low-income workers with

Table 2
Effect of minimum wage increases on extreme distress: BRFSS 2011 to 2019.

	Extreme distress			
	Men OLS	Women OLS	Men WLS	Women WLS
	(1)	(2)	(3)	(4)
Panel A: Low-income, no college education, age 25–54				
ln(Minimum wage)	−0.044***	−0.054***	−0.023	−0.080***
	(-0.075, −0.013)	(-0.092, −0.016)	(-0.054, 0.009)	(-0.134, −0.026)
Observations	45,271	46,932	45,271	46,932
Panel B: Placebo group (Low-income, college graduate or some college education, age 25–54)				
ln(Minimum wage)	0.011	−0.012	0.011	−0.021
	(-0.019, 0.041)	(-0.046, 0.022)	(-0.020, 0.041)	(-0.081, 0.039)
Observations	36,287	61,046	36,287	61,046
Panel C: Household income < $35,000, no college education, all ages and any household size				
ln(Minimum wage)	−0.039***	−0.035**	−0.017	−0.074***
	(-0.068, −0.010)	(-0.067, −0.002)	(-0.048, 0.013)	(-0.117, −0.031)
Observations	62,024	83,858	62,024	83,858

Notes: All models are estimated with a linear probability model and control for state characteristics, individual characteristics, month fixed effects, state fixed effects, year fixed effects, and cellphone-year interactions. For weighted least squares (WLS) regressions, BRFSS sample weights are applied. Standard errors are clustered around the state level, and 95% confidence intervals are shown in parentheses. "Low-income" is defined as household income < $20,000 for one-adult households and < $50,000 for households with two or more adults. *p < 0.1, **p < 0.05, ***p < 0.01.

Table 3
Effect of minimum wage increases on bad mental health days: BRFSS 2011 to 2019.

	Bad mental health days			
	Men OLS	Women OLS	Men WLS	Women WLS
	(1)	(2)	(3)	(4)
Panel A: Low-income, no college education, age 25–54				
Minimum wage	−1.321**	−1.405*	0.333	−2.327**
	(-2.491, −0.151)	(-2.924, 0.114)	(-1.776, 2.442)	(-4.420, −0.234)
Observations	45,271	46,932	45,271	46,932
Panel B: Placebo group (Low-income, college graduate or some college education, age 25–54)				
ln(Minimum wage)	0.136	−0.389	0.863	−1.291*
	(-0.894, 1.167)	(-1.747, 0.969)	(-0.411, 2.136)	(-2.803, 0.222)
Observations	36,287	61,046	36,287	61,046
Panel C: Household income < $35,000, no college education, all ages and any household size				
ln(Minimum wage)	−1.549***	−0.835	0.591	−1.625*
	(-2.596, −0.501)	(-2.073, 0.402)	(-1.135, 2.316)	(-3.536, 0.286)
Observations	62,024	83,858	62,024	83,858

Notes: All models control for state characteristics, individual characteristics, month fixed effects, state fixed effects, year fixed effects, and cellphone-year interactions. For weighted least squares (WLS) regressions, BRFSS sample weights are applied. Standard errors are clustered around the state level, and 95% confidence intervals are shown in parentheses. "Low-income" is defined as household income < $20,000 for one-adult households and < $50,000 for households with two or more adults. *p < 0.1, **p < 0.05, ***p < 0.01.

postsecondary education. Again, none of the coefficients are statistically significant, but the overall pattern is different from that of less educated workers, as there is no discontinuous drop in mental health measures at time 0.

Although it is reassuring to see that minimum wage hikes do not seem to reduce extreme distress among workers with postsecondary education, as they are not likely to be affected by minimum wages, failing to find significant effects of minimum wages even among workers with no postsecondary education is somewhat surprising. One possible reason is that the sample restriction based on household income and age exclude many minimum wage workers. To test this hypothesis, the sample is restricted to those whose income is less than $35,000 regardless of household size or age. Panel (c) of Fig. 1 shows the coefficients when these more inclusive criteria are used to define low-income workers with no postsecondary education, but the overall pattern is qualitatively similar to that of Panel (a).

Fig. 2 shows when the number of bad mental health days is used as the outcome variable. The qualitative pattern for low-income, less educated workers is similar to that of extreme distress, as shown in panel (a). As before, the coefficients are negative for periods $k \geq 0$, albeit statistically insignificant. For low-income workers with postsecondary education, no such pattern is detected, as shown in panel (b). Finally, when the sample restriction criteria for low-income workers are changed, as shown in panel (c), the lagged effects of higher minimum wages seem to disappear for women. Taken together, while the figures do not give any indications that higher minimum wages clearly improve mental health among low-income workers, these event study models exhibit parallel pre-trends for both men and women, regardless of their education levels, which provide support for the difference-in-differences design.

3.2. Difference-in-differences regressions

Table 2 provides the results from the linear probability regressions for extreme distress. For brevity, only the coefficients on the minimum wage are shown in the table, but Table A3 in the appendix shows the full regression results. The first and second columns of panel (a) show the results for men and women, respectively, and the coefficients suggest that a ten-percent increase in the minimum wage decreases the likelihood of extreme distress by 0.4 percentage points. They are statistically significant at the one percent level, indicating that higher minimum wages reduce the prevalence of extreme distress among these workers, presumably by reducing their financial strain. However, when the sample weight is applied, the coefficient is statistically significant only for women, as shown in the third and fourth columns. As mentioned above, using weighted-least squares (WLS) when weighting is unnecessary can lead to an imprecise estimate (Solon et al., 2015). This is in contrast with Horn et al. (2017), who find that the results do not differ whether weights are applied or not. This difference may be due to their sample including all income groups, which make the sample weight less relevant, as the sample weight is constructed using individual characteristics such as race, age, education levels, and marital status, that are highly correlated with income. However, as the BRFSS weights are based on observable characteristics (age, race, education, marital status, location, telephone source etc.) that are controlled for in the regressions, and given the efficiency issue associated with unnecessary weighting pointed out by Solon et al. (2015), it seems reasonable to assume that the OLS estimates may be preferable to the WLS estimates.

Panel (b) of Table 2 shows the results for low-income workers with postsecondary education, i.e. the placebo sample. The coefficients are not statistically significant, suggesting that minimum wage increases have little impact on mental health of these workers in the placebo sample. When a different sample restriction (Household income < $35,000, any household size, all ages and no postsecondary education) is used as a sensitivity check, the results remain substantially the same, as shown in panel (c), which give credence to the sample construction criteria used in panel (a).

Table 3 shows the results when the number of bad mental health days is used as the mental health outcome variable. Again, the full regression results are shown in Table A4 in the appendix. The magnitude indicates that a ten-percent increase in the minimum wage decreases the number of bad mental health days by 0.13–0.14. However, the coefficients are statistically significant at the five percent level for men but only at the ten percent level for women. These OLS results for bad mental health days are consistent with the view that having a job with a good wage is important especially for mental health of prime-age men.

The weak association between the minimum wage and bad mental health days among women is different from the finding by Horn et al. (2017), but as mentioned above, they use the BRFSS-provided weights in their estimate. While not the preferred specification in this study, the WLS estimate in the fourth column of Table 3 indicates that higher minimum wages are associated with lower bad mental health days for women. The WLS estimate for women suggests that a ten percent increase in the minimum wage is associated with 0.23 fewer bad mental health days for women, which is substantially larger than that in Horn et al. (2017), who find that 0.07 fewer bad mental health days for a ten percent increase in the minimum wage among women. Even if this study prefers OLS to WSL to be more reliable estimates, the results from WLS confirms that Horn et al. (2017) may be underestimating the mental health effect of the minimum wage among women for the reasons mentioned above.

As before, the placebo models do not find significant effects of minimum wages on bad mental health days among low-income workers with higher education levels, providing additional support for the difference-in-difference design. When the criteria for a treatment group is changed to all less-educated employees whose household income is less than $35,000 as a sensitivity check, the only statistically significant coefficient at the conventional level is for men from OLS, as shown in panel (c).

To summarize the main finding of the difference-in-differences regressions, both men and women with extreme levels of mental distress seem to benefit from higher minimum wages. Higher minimum wages also seem to reduce the average number of bad mental health days among men, though the association is statistically insignificant for women.

4. Conclusions

Previous studies have found that mental distress and deaths due to despair has increased among people without a college degree, presumably and partly due to their poor labor market prospects. Motivated by these studies, this study has examined the effects of minimum wages on mental health in the last decade among low-income, prime-age workers with no postsecondary education. The primary results suggest that higher minimum wages reduce the likelihood of extreme distress among less-educated workers at the low end of the income distribution.

To put the results into perspective, using the estimates from the difference-in-difference regression and taking the estimates at face value, increasing the federal minimum wage from $7.25 to $9.50 (approximately a 30 percent increase), as proposed by the Raise the Wage Act of 2021, which was introduced by House and Senate Democrats introduced in January but did not pass, would lead to approximately a 1.2–1.5 percentage point decline in the likelihood of extreme distress. Given that less than 5 percent of low-income, less-educated men and 8 percent of women in the sample reported extreme levels of mental distress, the magnitude is not trivial. Similarly, the average number of bad mental health days were 3.3 for men and 5.0 for women in the sample. A 30 percent increase in the minimum wage is expected to reduce the number of bad mental health days by 0.4. Therefore, the minimum wage could be an important policy tool that improves mental health among low-wage workers with no college education, especially those who are feeling extremely miserable.

It is important to state several limitations in this study. First, it should be noted the BRFSS survey data are phone-survey and self-reported, and thus the measures of mental health are not clinically validated. Second, this study does not address potential negative mental health effects of higher minimum wages on (1) workers who lose their job due to higher minimum wages and (2) unemployed people who are unable to find a job because employers are reluctant to pay higher minimum wages, even though previous studies have found that jobless people tend to report extremely low levels of emotional well-being (Blanchflower & Oswald, 2020; Krueger, 2017). Third, the data do not allow minimum-wage workers to be identified; rather, workers who are likely to work minimum-wage jobs are analyzed.

Finally, it should be noted that several recent studies document issues with two-way fixed-effect regressions in the presence of heterogeneous treatment effects in difference-in-differences and event studies with variation in treatment timing, including Sun and Abraham (2021), Callaway and Sant'Anna (2021), and Goodman-Bacon (2021). While this study does not utilize approaches suggested by those studies, as it seems that a consensus has yet been reached on how to account for heterogeneous treatment effects in panel studies, readers should be aware of the emerging literature in this field. Nevertheless, the main finding in this paper points to the importance of considering the positive mental health effects when evaluating the impact of higher minimum wages in the United States.

Compliance with ethical standards

The author declares that he has no conflict of interest.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

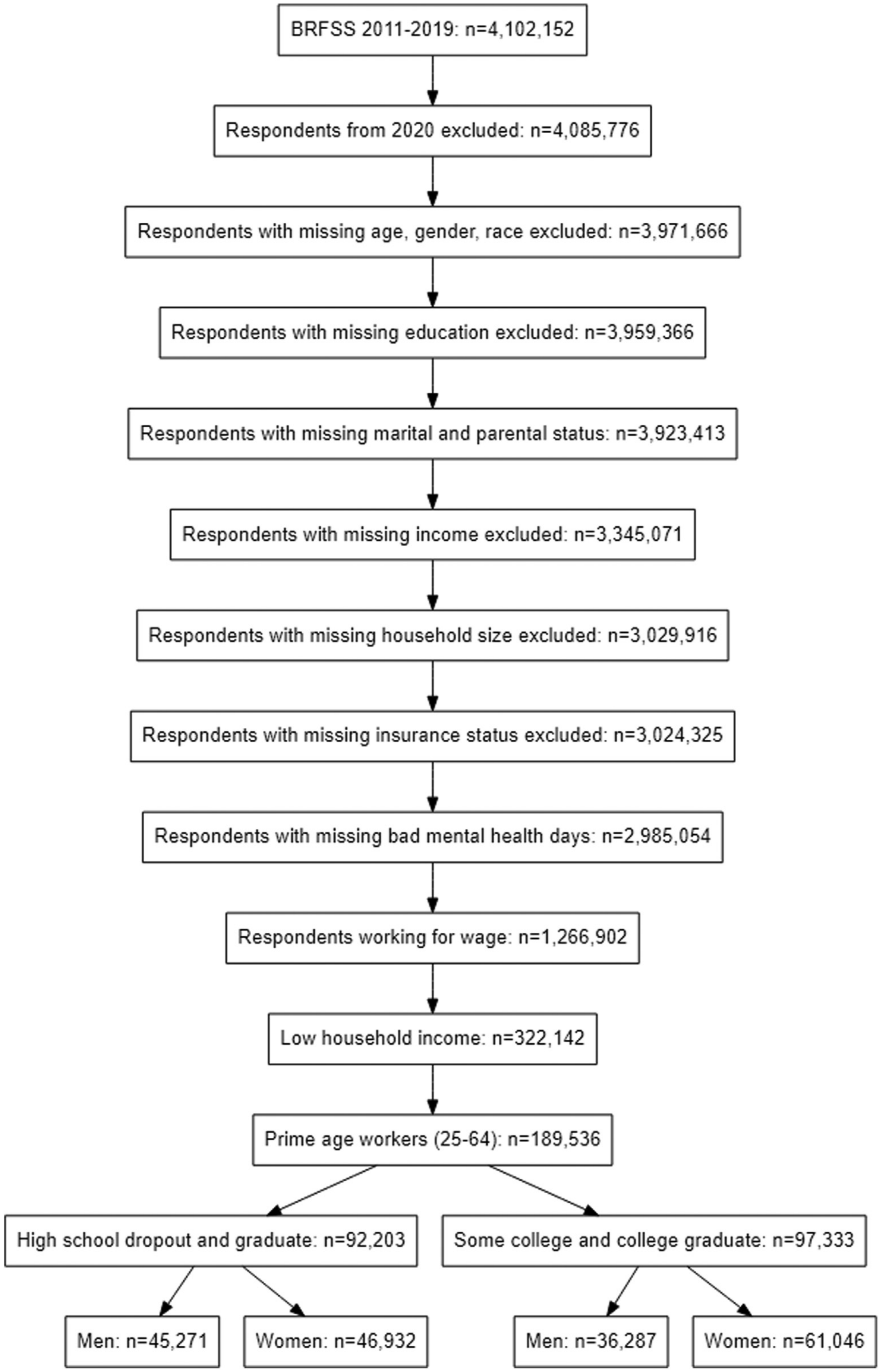

Fig. A1. Participant flow diagram: BRFSS 2011–2019.

Table A1
Effective minimum wage by state, 2011–2019

State	2011	2012	2013	2014	2015	2016	2017	2018	2019
Alabama	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Alaska	7.75	7.75	7.75	7.75	8.75+	9.75+	9.80+	9.84+	10.19+
Arizona	7.35	7.65+	7.80+	7.90+	8.05+	8.05	10.00+	10.50+	12.00+
Arkansas	7.25	7.25	7.25	7.25	7.50+	8.00+	8.50+	8.50	9.25+
California	8.00	8.00	8.00	9.00+	9.00	10.00+	10.00	11.00+	12.00+
Colorado	7.36	7.64+	7.78+	8.00+	8.23+	8.31+	9.30+	10.20+	12.00+
Connecticut	8.25	8.25	8.25	8.70+	9.15+	9.60+	10.10+	10.10	11.00+
Delaware	7.25	7.25	7.25	7.75+	8.25+	8.25	8.25	8.25	9.25+
District of Columbia	8.25	8.25	8.25	9.50+	10.50+	11.50+	11.50	13.25+	14.00+
Florida	7.25	7.67+	7.79+	7.93+	8.05+	8.05	8.10+	8.25+	8.56+
Georgia	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Hawaii	7.25	7.25	7.25	7.25	7.75+	8.50+	9.25+	10.10+	10.10
Idaho	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Illinois	8.25	8.25	8.25	8.25	8.25	8.25	8.25	8.25	9.25+
Indiana	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Iowa	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Kansas	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Kentucky	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Louisiana	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Maine	7.50	7.50	7.50	7.50	7.50	7.50	9.00+	10.00+	12.00+
Maryland	7.25	7.25	7.25	7.25	8.25+	8.75+	8.75	10.10+	11.00+
Massachusetts	8.00	8.00	8.00	8.00	9.00+	10.00+	11.00+	11.00	12.75+
Michigan	7.40	7.40	7.40	8.15+	8.15	8.50+	8.90+	9.25+	9.65+
Minnesota	7.25	7.25	7.25	8.00+	9.00+	9.50+	9.50	9.86+	10.00+
Mississippi	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Missouri	7.25	7.25	7.35+	7.50+	7.65+	7.65	7.70+	7.85+	9.45+
Montana	7.35	7.65+	7.80+	7.90+	8.05+	8.05	8.15+	8.30+	8.65+
Nebraska	7.25	7.25	7.25	7.25	8.00+	9.00+	9.00	9.00	9.00
Nevada	8.25	8.25	8.25	8.25	8.25	8.25	8.25	8.25	8.25
New Hampshire	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
New Jersey	7.25	7.25	7.25	8.25+	8.38+	8.38	8.44+	8.60+	11.00+
New Mexico	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50	9.00+
New York	7.25	7.25	7.25	8.00+	8.75+	9.00+	9.70+	10.40+	11.80+
North Carolina	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
North Dakota	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Ohio	7.40	7.70+	7.85+	7.95+	8.10+	8.10	8.15+	8.30+	8.70+
Oklahoma	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Oregon	8.50	8.80+	8.95+	9.10+	9.25+	9.75+	9.75	10.75+	11.25+
Pennsylvania	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Rhode Island	7.40	7.40	7.75+	8.00+	9.00+	9.60+	9.60	10.10+	10.50+
South Carolina	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
South Dakota	7.25	7.25	7.25	7.25	8.50+	8.55+	8.65+	8.85+	9.30+
Tennessee	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Texas	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Utah	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Vermont	8.15	8.46+	8.60+	8.73+	9.15+	9.60+	10.00+	10.50+	10.96+
Virginia	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Washington	8.67	9.04+	9.19+	9.32+	9.47+	9.47	11.00+	11.50+	13.50+
West Virginia	7.25	7.25	7.25	7.25	8.00+	8.75+	8.75	8.75	8.75
Wisconsin	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Wyoming	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25

Note: Wage rates are for January 1 of each year. "+" indicates an increase over the previous year's rate.

Table A2
Event study variables: Oregon and Texas

Year	State	Minimum Wage	Change	−3	−2	−1	0	+1	+2	+3
2009	Oregon	8.40	0.45							
2010	Oregon	8.40	0.00							
2011	Oregon	8.50	0.10	3.05	0.15	0.30	0.10	0.00	0.45	0.45
2012	Oregon	8.80	0.30	2.90	0.15	0.15	0.30	0.10	0.00	0.90
2013	Oregon	8.95	0.15	2.75	0.15	0.15	0.15	0.30	0.10	0.90
2014	Oregon	9.10	0.15	2.25	0.50	0.15	0.15	0.15	0.30	1.00
2015	Oregon	9.25	0.15	2.25	0.00	0.50	0.15	0.15	0.15	1.30
2016	Oregon	9.75	0.50	1.25	1.00	0.00	0.50	0.15	0.15	1.45
2017	Oregon	9.75	0.00	0.75	0.50	1.00	0.00	0.50	0.15	1.60
2018	Oregon	10.75	1.00	0.00	0.75	0.50	1.00	0.00	0.50	1.75
2019	Oregon	11.25	0.50	0.00	0.00	0.75	0.50	1.00	0.00	2.25
2020	Oregon	12.00	0.75							
2021	Oregon	12.00	0.00							
2009	Texas	6.55	0.70							
2010	Texas	7.25	0.70							

(continued on next column)

Table A2 (*continued*)

Year	State	Minimum Wage	Change	−3	−2	−1	0	+1	+2	+3
2011	Texas	7.25	0.00	0.00	0.00	0.00	0.00	0.70	0.70	0.70
2012	Texas	7.25	0.00	0.00	0.00	0.00	0.00	0.00	0.70	1.40
2013	Texas	7.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.10
2014	Texas	7.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.10
2015	Texas	7.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.10
2016	Texas	7.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.10
2017	Texas	7.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.10
2018	Texas	7.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.10
2019	Texas	7.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.10
2020	Texas	7.25	0.00							
2021	Texas	7.25	0.00							

Notes: These minimum wage changes are nominal changes. They are converted to real minimum wage changes (adjusted for inflation to January 2021 dollars) in the analysis.

Table A3
Effect of minimum wage increases on extreme distress: BRFSS 2011–2019

	Extreme distress			
	Men OLS	Women OLS	Men WLS	Women WLS
	(1)	(2)	(3)	(4)
ln(Minimum wage)	−0.044***	−0.054***	−0.023	−0.080***
	(-0.075, −0.013)	(-0.092, −0.016)	(-0.054, 0.009)	(-0.134, −0.026)
High school graduate	−0.014***	−0.022***	−0.007**	−0.021***
	(-0.020, −0.008)	(-0.029, −0.015)	(-0.014, −0.0001)	(-0.031, −0.010)
Black	−0.018***	−0.041***	−0.019***	−0.030***
	(-0.026, −0.010)	(-0.053, −0.029)	(-0.033, −0.005)	(-0.049, −0.010)
Hispanic	−0.033***	−0.052***	−0.034***	−0.055***
	(-0.040, −0.027)	(-0.060, −0.044)	(-0.047, −0.021)	(-0.067, −0.043)
Other	0.001	−0.014**	−0.005	−0.027***
	(-0.010, 0.011)	(-0.028, −0.001)	(-0.019, 0.009)	(-0.045, −0.009)
Age 30–34	−0.008*	−0.004	−0.015**	0.006
	(-0.016, 0.0001)	(-0.013, 0.006)	(-0.029, −0.00003)	(-0.007, 0.019)
Age 35–39	−0.004	−0.007	−0.010	0.005
	(-0.012, 0.003)	(-0.017, 0.003)	(-0.023, 0.003)	(-0.010, 0.019)
Age 40–44	−0.010**	−0.011***	−0.016**	0.001
	(-0.019, −0.002)	(-0.019, −0.003)	(-0.031, −0.002)	(-0.008, 0.010)
Age 45–49	−0.013***	−0.008*	−0.013	−0.001
	(-0.020, −0.005)	(-0.018, 0.001)	(-0.029, 0.003)	(-0.013, 0.011)
Age 50–54	−0.023***	−0.018***	−0.033***	−0.004
	(-0.030, −0.015)	(-0.027, −0.008)	(-0.047, −0.020)	(-0.015, 0.006)
Divorced	0.022***	0.035***	0.025***	0.021***
	(0.014, 0.029)	(0.028, 0.042)	(0.011, 0.038)	(0.010, 0.031)
Widowed	0.049***	0.051***	0.068**	0.046***
	(0.020, 0.077)	(0.038, 0.064)	(0.015, 0.120)	(0.024, 0.069)
Separated	0.044***	0.035***	0.024***	0.027***
	(0.030, 0.058)	(0.024, 0.046)	(0.007, 0.041)	(0.016, 0.037)
Never married	0.009***	0.017***	0.003	0.015***
	(0.003, 0.014)	(0.010, 0.024)	(-0.005, 0.011)	(0.004, 0.026)
Cohabitating	0.005	0.006	−0.002	−0.002
	(-0.003, 0.013)	(-0.003, 0.014)	(-0.012, 0.007)	(-0.016, 0.012)
Have children	−0.004	−0.004	−0.008***	−0.004
	(-0.009, 0.001)	(-0.011, 0.003)	(-0.014, −0.003)	(-0.012, 0.004)
Health insurance	−0.006**	−0.011***	−0.007**	−0.014***
	(-0.011, −0.001)	(-0.017, −0.005)	(-0.012, −0.001)	(-0.024, −0.004)
State poverty	0.001	−0.004**	−0.002	−0.009***
	(-0.003, 0.005)	(-0.008, −0.0002)	(-0.009, 0.004)	(-0.015, −0.003)
State unemployment	−0.001	0.007***	0.001	0.013***
	(-0.005, 0.003)	(0.003, 0.011)	(-0.004, 0.007)	(0.007, 0.020)
Medicaid expansion	0.002	0.006	−0.001	0.008
	(-0.008, 0.011)	(-0.003, 0.014)	(-0.012, 0.010)	(-0.008, 0.023)
ln(TANF benefit)	−0.017	0.019	−0.013	−0.023
	(-0.051, 0.017)	(-0.049, 0.087)	(-0.070, 0.045)	(-0.069, 0.023)
ln(SNAP benefit)	0.084**	−0.0001	0.071	0.077
	(0.005, 0.163)	(-0.100, 0.100)	(-0.098, 0.240)	(-0.084, 0.237)
State EITC	−0.006	−0.014	−0.003	0.016*
	(-0.021, 0.010)	(-0.036, 0.007)	(-0.015, 0.010)	(-0.002, 0.035)
SSI	−1.738	−0.793	0.489	1.897
	(-6.153, 2.677)	(-4.285, 2.700)	(-5.291, 6.270)	(-5.304, 9.098)
ln(Population)	−0.166*	−0.109	−0.298***	0.021

(*continued on next column*)

Table A3 (*continued*)

	Extreme distress			
	Men OLS	Women OLS	Men WLS	Women WLS
	(1)	(2)	(3)	(4)
	(-0.352, 0.021)	(-0.336, 0.118)	(-0.509, −0.087)	(-0.305, 0.348)
Observations	45,271	46,932	45,271	46,932
Adjusted R^2	0.009	0.014	0.015	0.017

All models are estimated with a linear probability model and control for month fixed effects, state fixed effects, year fixed effects, and cellphone-year interactions. For weighted least squares (WLS) regressions, BRFSS sample weights are applied. Standard errors are clustered around the state level, and 95% confidence intervals are shown in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

Table A4
Effect of minimum wage increases on bad mental health days: BRFSS 2011–2019

	Bad mental health days			
	Men OLS	Women OLS	Men WLS	Women WLS
	(1)	(2)	(3)	(4)
ln(Minimum wage)	−1.321**	−1.405*	0.333	−2.327**
	(-2.491, −0.151)	(-2.924, 0.114)	(-1.776, 2.442)	(-4.420, −0.234)
High school graduate	−0.486***	−0.682***	−0.285**	−0.616***
	(-0.696, −0.276)	(-0.928, −0.435)	(-0.560, −0.011)	(-0.989, −0.244)
Black	−1.054***	−2.098***	−1.124***	−1.743***
	(-1.334, −0.774)	(-2.535, −1.661)	(-1.623, −0.626)	(-2.313, −1.173)
Hispanic	−1.872***	−2.827***	−1.884***	−2.997***
	(-2.105, −1.639)	(-3.169, −2.485)	(-2.226, −1.543)	(-3.413, −2.582)
Other	−0.147	−1.063***	−0.752***	−1.320***
	(-0.547, 0.253)	(-1.690, −0.436)	(-1.237, −0.266)	(-1.956, −0.684)
Age 30–34	−0.394***	−0.265	−0.435**	0.035
	(-0.660, −0.129)	(-0.611, 0.081)	(-0.837, −0.033)	(-0.434, 0.503)
Age 35–39	−0.436***	−0.446***	−0.579***	−0.054
	(-0.711, −0.160)	(-0.775, −0.117)	(-0.876, −0.283)	(-0.599, 0.492)
Age 40–44	−0.815***	−0.756***	−0.768***	−0.228
	(-1.097, −0.533)	(-1.084, −0.429)	(-1.172, −0.363)	(-0.653, 0.196)
Age 45–49	−0.965***	−0.693***	−0.779***	−0.336
	(-1.244, −0.686)	(-1.037, −0.349)	(-1.225, −0.332)	(-0.754, 0.082)
Age 50–54	−1.351***	−1.173***	−1.584***	−0.701***
	(-1.602, −1.100)	(-1.540, −0.807)	(-1.976, −1.192)	(-1.165, −0.236)
Divorced	1.191***	1.635***	1.068***	1.255***
	(0.980, 1.403)	(1.402, 1.867)	(0.708, 1.427)	(0.813, 1.697)
Widowed	2.223***	2.087***	2.246**	2.132***
	(1.168, 3.279)	(1.630, 2.544)	(0.474, 4.019)	(1.388, 2.876)
Separated	2.155***	1.769***	1.453***	1.454***
	(1.692, 2.618)	(1.348, 2.190)	(0.775, 2.132)	(1.074, 1.835)
Never married	0.781***	0.900***	0.665***	0.989***
	(0.567, 0.995)	(0.666, 1.135)	(0.301, 1.028)	(0.615, 1.363)
Cohabitating	0.564***	0.845***	0.298	0.403
	(0.251, 0.877)	(0.473, 1.217)	(-0.127, 0.724)	(-0.094, 0.900)
Have children	−0.141*	−0.147	−0.243*	−0.131
	(-0.308, 0.026)	(-0.376, 0.082)	(-0.496, 0.009)	(-0.417, 0.154)
Health insurance	−0.330***	−0.529***	−0.342***	−0.584***
	(-0.496, −0.164)	(-0.805, −0.254)	(-0.539, −0.145)	(-0.970, −0.198)
State poverty	0.040	−0.105	0.043	−0.218*
	(-0.086, 0.167)	(-0.247, 0.037)	(-0.189, 0.275)	(-0.452, 0.015)
State unemployment	−0.010	0.263***	0.059	0.488***
	(-0.153, 0.133)	(0.124, 0.401)	(-0.161, 0.279)	(0.209, 0.768)
Medicaid expansion	0.252	0.248	0.162	0.267
	(-0.069, 0.573)	(-0.070, 0.566)	(-0.245, 0.570)	(-0.191, 0.726)
ln(TANF benefit)	−0.805	0.647	−0.300	−1.454*
	(-2.054, 0.445)	(-1.771, 3.065)	(-2.600, 1.999)	(-3.046, 0.139)
ln(SNAP benefit)	0.249	0.497	1.466	3.268
	(-2.688, 3.186)	(-3.290, 4.284)	(-3.976, 6.908)	(-4.657, 11.194)
State EITC	−0.988***	−1.891***	−0.988***	−1.022**
	(-1.604, −0.371)	(-2.578, −1.204)	(-1.512, −0.463)	(-1.862, −0.182)
SSI	−17.885	−43.625	−38.027	50.838
	(-178.542, 142.773)	(-186.747, 99.498)	(-283.375, 207.321)	(-225.874, 327.550)
ln(Population)	−7.700**	−4.304	−7.757	1.323
	(-14.554, −0.846)	(-12.718, 4.109)	(-20.838, 5.325)	(-11.510, 14.156)

(*continued on next column*)

Table A4 (*continued*)

	Bad mental health days			
	Men OLS	Women OLS	Men WLS	Women WLS
	(1)	(2)	(3)	(4)
Observations	45,271	46,932	45,271	46,932
Adjusted R^2	0.023	0.030	0.027	0.035

All models control for month fixed effects, state fixed effects, year fixed effects, and cellphone-year interactions. For weighted least squares (WLS) regressions, BRFSS sample weights are applied. Standard errors are clustered around the state level, and 95% confidence intervals are shown in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

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