The Minimum Wage and Children's Mental Health

Online Appendix

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Outcome Variables in NSCH

Below, we provide the question wording (per the NSCH and YRBSS documentation) and coding of all outcomes. Note that the code evaluates the first condition for a match; if and only if a match is not made on the first condition does it proceed to the next. Thus, respondents can only meet one condition. Any respondents missing a given outcome were dropped pairwise from analyses.

Table A1. Question wording and coding of all mental health outcomes.

Survey	Outcome	Question wording	Coding
NSCH (All children)	**Depression**	Variable name: K2Q32A "Has a doctor or other health care provider EVER told you that this child has?...Depression?" 1 = Yes 2 = No Variable name: K2Q32B "If yes, does this child CURRENTLY have the condition?" 1 = Yes 2 = No Skip logic: Skip if K2Q32A=2	1 if K2Q32B = 1 Otherwise, 0 if K2Q32B = 2 or if K2Q32A = 1 or 2 That is, a child who currently has depression is coded as "1"; any child who otherwise answered the questions about depression is coded as "0".

Survey	**Outcome**	**Question wording**	**Coding**
NSCH (All children)	**Anxiety**	***Variable name: K2Q33A*** "Has a doctor or other health care provider EVER told you that this child has?...Anxiety Problems?" 1 = Yes 2 = No ***Variable name: K2Q33B*** "If yes, does this child CURRENTLY have the condition?" 1 = Yes 2 = No *Skip logic: Skip if K2Q33A=2*	1 if K2Q33B = 1 Otherwise, 0 if K2Q33B = 2 or if K2Q33A = 1 or 2

Survey	Outcome	Question wording	Coding
NSCH (All children)	**ADD/ADHD**	***Variable name: K2Q31A*** "Has a doctor or other health care provider EVER told you that this child has?...Attention Deficit Disorder or Attention-Deficit/Hyperactivity Disorder, that is, ADD or ADHD?" 1 = Yes 2 = No ***Variable name: K2Q31B*** "If yes, does this child CURRENTLY have the condition?" 1 = Yes 2 = No *Skip logic: Skip if K2Q31A=2*	1 if K2Q31B = 1 Otherwise, 0 if K2Q31B = 2 or if K2Q31A = 1 or 2

Survey	Outcome	Question wording	Coding
NSCH (All children)	**Behavioral prob.**	***Variable name: K2Q34A*** "Has a doctor, other health care provider, or educator EVER told you that this child has?...Behavioral or Conduct Problems?...Examples of educators are teachers and school nurses." 1 = Yes 2 = No ***Variable name: K2Q34B*** "If yes, does this child CURRENTLY have the condition?" 1 = Yes 2 = No *Skip logic: Skip if K2Q34A=2*	1 if K2Q34B = 1 Otherwise, 0 if K2Q34B = 2 or if K2Q34A = 1 or 2
NSCH (All children)	**Digestive issues**	***Variable name: STOMACH*** "DURING THE PAST 12 MONTHS, has this child had FREQUENT or CHRONIC difficulty with any of the following?...Digesting food, including stomach/intestinal problems, constipation, or diarrhea" 1 = Yes 2 = No	1 if STOMACH = 1 Otherwise, 0 if STOMACH = 2

Survey	Outcome	Question wording	Coding
NSCH **(All children)**	**Any unmet care**	***Variable name: K4Q27*** "DURING THE PAST 12 MONTHS, was there any time when this child needed health care but it was not received?...Health care includes medical care, dental care, vision care, and mental health services." 1 = Yes 2 = No	1 if K4Q27 = 1 Otherwise, 0 if K4Q27 = 2
NSCH **(All children)**	**Unmet mental care**	***Variable name: K4Q27*** "DURING THE PAST 12 MONTHS, was there any time when this child needed health care but it was not received?...Health care includes medical care, dental care, vision care, and mental health services." 1 = Yes 2 = No ***Variable name: K4Q28X04*** "Which types of care was/were not received?...Mental Health Services" 1 = selected 2 = not selected *Skip logic: Skip if K4Q27=2*	1 if K4Q28X04 = 1 Otherwise, 0 if K4Q27 = 1 or 2

Survey	Outcome	Question wording	Coding
NSCH (All children)	**7+ school absences**	***Variable name: K7Q02R_R*** "DURING THE PAST 12 MONTHS, about how many days did this child miss school because of an illness or injury? Include days missed from any formal home schooling." 1 = No missed school days 2 = 1 - 3 days 3 = 4 - 6 days 4 = 7 - 10 days 5 = 11 or more days 6 = This child was not enrolled in school *Skip logic: If FORMTYPE in ('T2','T3')*	1 if K7Q02R_R = 4–5 Otherwise, 0 if K7Q02R_R = 1–3, 6
NSCH (All children)	**Child employment**	***Variable name: K7Q38*** "DURING THE PAST 12 MONTHS, did this child participate in:...Any paid work including regular jobs as well as babysitting, cutting grass, or other occasional work?" 1 = Yes 2 = No *Skip logic: If FORMTYPE in ('T2','T3')*	1 if K7Q38 = 1 Otherwise, 0 if K7Q48 = 2

Survey	Outcome	Question wording	Coding
YRBSS (Adolescents)	**Sad or hopeless**	***Variable name: Q25*** "During the past 12 months, did you ever feel so sad or hopeless almost every day for two weeks or more in a row that you stopped doing some usual activities?" A. Yes B. No	1 if Q25 = A (1) Otherwise, 0 if Q25 = B (2)
YRBSS (Adolescents)	**Considered suicide**	***Variable name: Q26*** "During the past 12 months, did you ever seriously consider attempting suicide?" A. Yes B. No	1 if Q26 = A (1) Otherwise, 0 if Q26 = B (2)
YRBSS (Adolescents)	**Attempted suicide**	***Variable name: Q28*** "During the past 12 months, how many times did you actually attempt suicide?" A. 0 times B. 1 time C. 2 or 3 times D. 4 or 5 times E. 6 or more times	1 if Q28 = B–E (2–5) Otherwise, 0 if Q28 = A (1)

Survey	Outcome	Question wording	Coding
YRBSS (Adolescents)	**Recent alcohol**	***Variable name: Q41*** "During the past 30 days, on how many days did you have at least one drink of alcohol?" A. 0 days B. 1 or 2 days C. 3 to 5 days D. 6 to 9 days E. 10 to 19 days F. 20 to 29 days G. All 30 days	1 if Q47 = B–G (2–7) Otherwise, 0 if Q41 = A (1)
YRBSS (Adolescents)	**Recent marijuana**	***Variable name: Q47*** "During the past 30 days, how many times did you use marijuana?" A. 0 times B. 1 or 2 times C. 3 to 9 times D. 10 to 19 times E. 20 to 39 times F. 40 or more times	1 if Q47 = B–F (2–6) Otherwise, 0 if Q47 = 1

Survey	Outcome	Question wording	Coding
YRBSS (Adolescents)	**Physical fight**	***Variable name: Q17*** "During the past 12 months, how many times were you in a physical fight?" A. 0 times B. 1 time C. 2 or 3 times D. 4 or 5 times E. 6 or 7 times F. 8 or 9 times G. 10 or 11 times H. 12 or more times	1 if Q17 = B–H (2–8) Otherwise, 0 if Q17 = A (1)

Other State Policy Controls

We control for several competing state-level policies that vary over time and could affect the financial well-being of low-income families. These data were collected from numerous sources, which we document below alongside any coding decisions we made for these covariates. The raw and cleaned data tables are provided with the paper's replication materials.

The Medicaid income eligibility limits were sourced from the Kaiser Family Foundation (https://www.kff.org/statedata/collection/trends-in-medicaid-income-eligibility-limits/). Data for 2001 and 2007 were unavailable, so we used the income limits from October 2000 and July 2006, respectively. For 2009, we used the limits from January, not December, in keeping with the other years. Tennessee had no upper limit for some years, so we used a value of 400% FPL.

The earned income tax credit (EITC) covariates were based on data from the Tax Policy Center, run by the Urban Institute and Brookings Institution (https://www.taxpolicycenter.org/statistics/state-eitc-percentage-federal-eitc). For the presence of a state EITC, we coded any state that had a non-zero ratio of state-to-federal EITC as "yes" and all other states as "no." For states with multiple rates, we used the most generous benefit for which a household with children might be eligible. For example, for many years, Wisconsin had three rates corresponding to the number of dependent children, so we used the highest of the three. Any state without an EITC was assigned a rate of 0. The Tax Policy Center was missing data for 2011, so we used those from 2010. When coding whether a state's EITC was refundable, any state that was at least "partially" refundable was coded as 1; all other states (including those without an EITC) were coded as 0.

The Temporary Assistance for Needy Families (TANF) benefits were adapted from the Urban Institute's Welfare Rules Database (https://wrd.urban.org/wrd/Query/query.cfm). We triangulated the maximum benefits (in dollars) for a family of 3 by using the database itself and a summary table compiled through 2020 (Table L5). In cases of uncertainty or disagreement between the two, we typically used the values reported in the summary table. The database was missing values for Colorado from 2001 to 2007; since the summary table reported the same value in both 1996 and 2004 ($365), we used $365 for 2001 to 2007. All other decisions regarding the TANF benefits are documented in the cleaned data table in the replication package.

Inequities in Mental Health by Household Income

To describe the cross-sectional economic inequities in mental health, we used the NSCH, as it provides household federal poverty levels (FPL) based on self-reported or imputed household income. The YRBSS does not provide household income, so we cannot perform a similar exercise with that survey. We divided households into five income categories: less than 100% FPL, 100% to 199%, 200% to 299%, 300% to 399%, and 400% FPL or greater. Then, we used ordinary least squares (OLS) models to estimate the differences in mental health outcomes between them, with adjustments for the child's age, sex, race/ethnicity, family structure, the highest education of any adult in the household, and household nativity (i.e. the individual-level covariates included in the paper's statistical models), plus state and year fixed effects. These adjustments allowed us to compare children of different household incomes but similar demographics within a given state and year. We also used the NSCH survey weights and clustered standard errors (SEs) at the state level. All models were estimated using the "lfe" package (v. 2.8) in R.

The cross-sectional economic inequities are depicted in **Figure A1**. For example, children living in poverty suffered depression at a rate 2.6 percentage points (pp) higher than children living in households above 400% FPL. For the remaining outcomes, the corresponding inequities were +2.9 pp for anxiety, +1.7 pp for ADD/ADHD, +3.9 pp for behavioral problems, +3.3 pp for digestive issues, +3.4 pp for unmet medical care of any kind, +1.2 pp for unmet mental health care, and +5.8 pp for 7+ school absences. Meanwhile, children living in poverty were employed at a rate 4.0 pp lower than children above 400% FPL. Comparisons between the remaining income levels and 400%+ FPL with 95% confidence intervals (CIs) are provided in the figure.

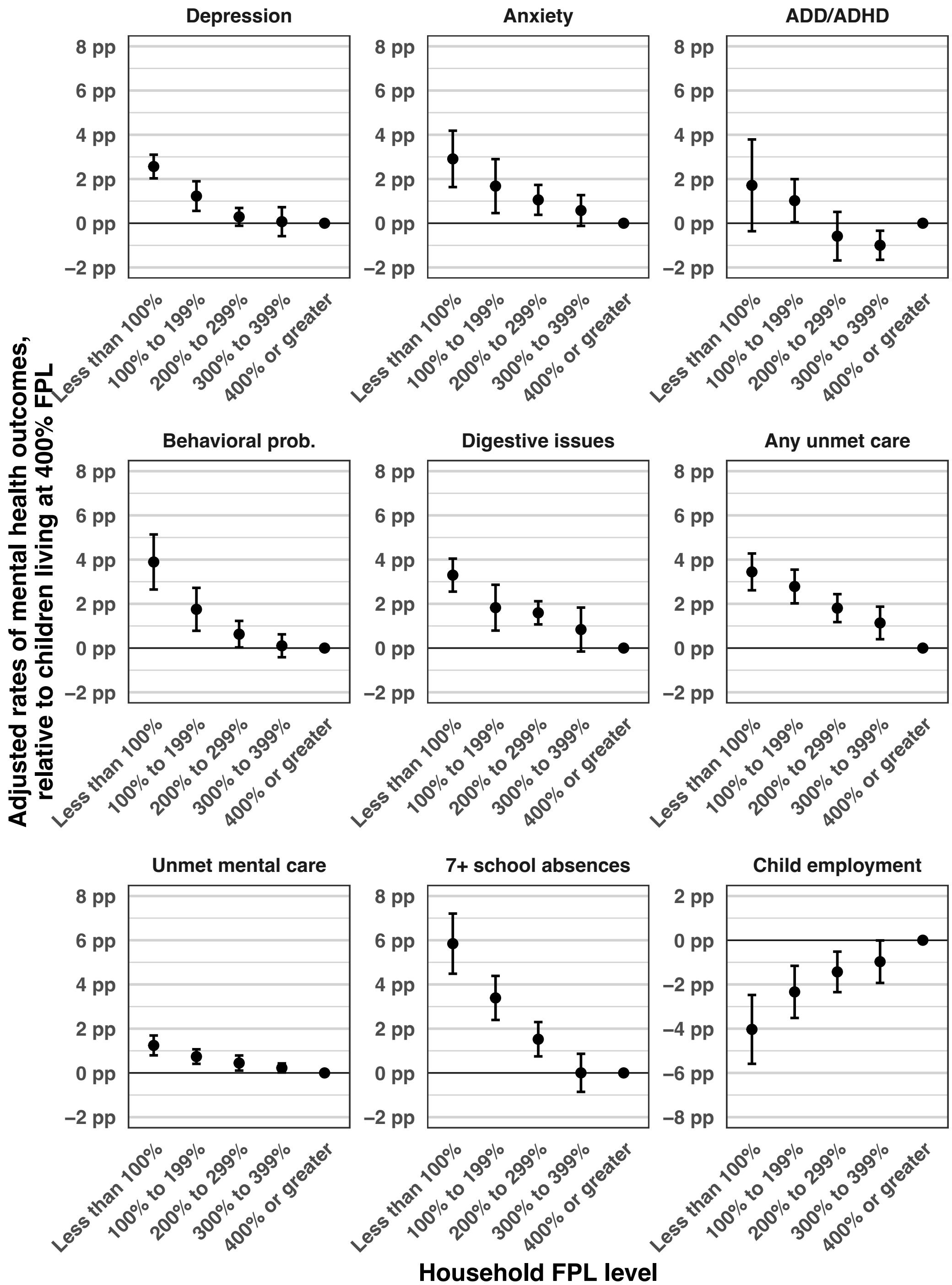

Figure A1. Adjusted mental health inequities by household income.

Notes: Based on cross-sectional OLS models that compare the indicated income categories to 400% FPL or greater. Models are adjusted for individual-level demographics per **Table A2**, as well as state and year fixed effects. SEs are flustered at the state level. 95% CIs are provided.

Two-Way Fixed Effects (TWFE) Specifications

The main TWFE models were specified as follows:

$$Y_{ist} = \beta_1(min.wage)_{st} + \boldsymbol{\beta X_{ist}} + \boldsymbol{\beta Z_{st}} + \Delta_s + \tau_t + \varepsilon_{ist}$$

where Y_{ist} is the mental health outcome for individual *i* in state *s* in year *t*; $(min.\ wage)_{st}$ is the effective minimum wage in a state-year, X_{ist} is a vector of individual-level controls (which vary by survey; listed below); Z_{st} is a vector of time-variant state-level policies (see above); Δ_s is the time-invariant state fixed effect; τ_t is the year (or age-by-year) fixed effect; and ε_{ist} is the error.

The individual- and state-level controls included in the fully adjusted models are listed in **Table A2**. Note that the YRBSS has fewer available covariates than the NSCH. All models use the NSCH or YRBSS survey weights and cluster SEs at the state level, except as noted. We use the "lfe" package (v. 2.8) in R to estimate models by OLS, again except as noted.

Table A2. Covariates included in TWFE models.

Level	NSCH models	YRBSS models
Individual	Child's age	Adolescent's age
	Child's sex	Adolescent's sex
	Child's race/ethnicity	Adolescent's race/ethnicity
	Family structure	Adolescent's grade
	Highest education of any adult in household	
	Household nativity	
State	Medicaid income limits for ages 1–5*	Medicaid income limits for ages 1–5*
	Medicaid income limits for ages 6–18*	Medicaid income limits for ages 6–18*
	Presence of state EITC	Presence of state EITC
	State EITC as percent of federal EITC*	State EITC as percent of federal EITC*
	State EITC refundability	State EITC refundability
	Maximum TANF benefit for family of 3*	Maximum TANF benefit for family of 3*
Fixed effects	State	State
	Year	Adolescent's age-by-year**

Notes:

*Treated as continuous variables. All other variables are treated as categorical.

**The age-by-year control was constructed by interacting the adolescent's age with the year of the survey. For example, it had levels for "age 12 in 2001," "age 12 in 2003," "age 12 in 2005," etc., to reflect the distinct generational experiences throughout the 19-year study period. That is, it reflects the fact that the experience of being a 12-year-old is different in 2001 than in 2019.

TWFE Corrections for Multiple Comparisons

The risk of type I errors, or false positives due to chance, increases with the number of statistical tests. Given that we examine 15 outcomes, many sub-populations, and several alternate specifications, the risk of a false positive in our study is considerably greater than 5%.

To reduce this risk, we implement a Bonferroni correction of all CIs presented in the appendix. This procedure caps the family-wise error rate for all 15 outcomes at 5% without assuming independence across them. The Bonferroni correction is conservative, resulting in a true family-wise error rate likely lower than 5%,[1] but it allows us to rule out the largest possible associations between the minimum wage and each mental health outcome. We use an alpha of 0.05/15 = 0.0033 for all TWFE models, or a 99.7% CI, corresponding to a critical value of 2.94. (For the difference-in-differences and event study models, we only examine 6 outcomes, so we use an alpha of 0.05/6 = 0.0083, or a 99.2% CI and a corresponding critical value of 2.64.)

The Bonferroni-corrected CIs for the main models are presented in **Figures A2** and **A3**. They are moderately wider than the uncorrected CIs. Even so, we can continue to rule out meaningfully large associations between the minimum wage and all our mental health outcomes. For all other analyses in the appendix, we provide both the uncorrected and corrected CIs.

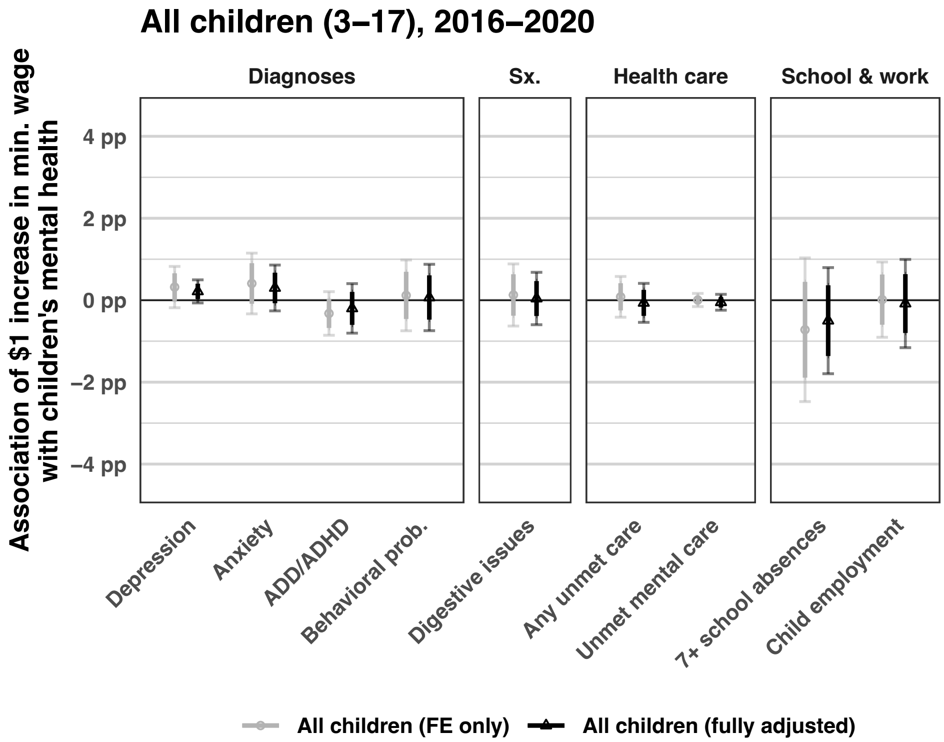

Figure A2. Main TWFE models with Bonferroni corrections for the NSCH.

Notes: Re-estimation of the main OLS TWFE models with Bonferroni corrections for 15 outcomes. The thick lines provide the uncorrected 95% CIs (i.e. with critical values of 1.96), while the thin ones provide the Bonferroni-corrected 99.7% CIs (i.e. with critical values of 2.94). All models include state and year fixed effects; fully adjusted models add individual- and state-level covariates per **Table A2**. SEs are clustered at the state level. N = 114,163 to 141,094.

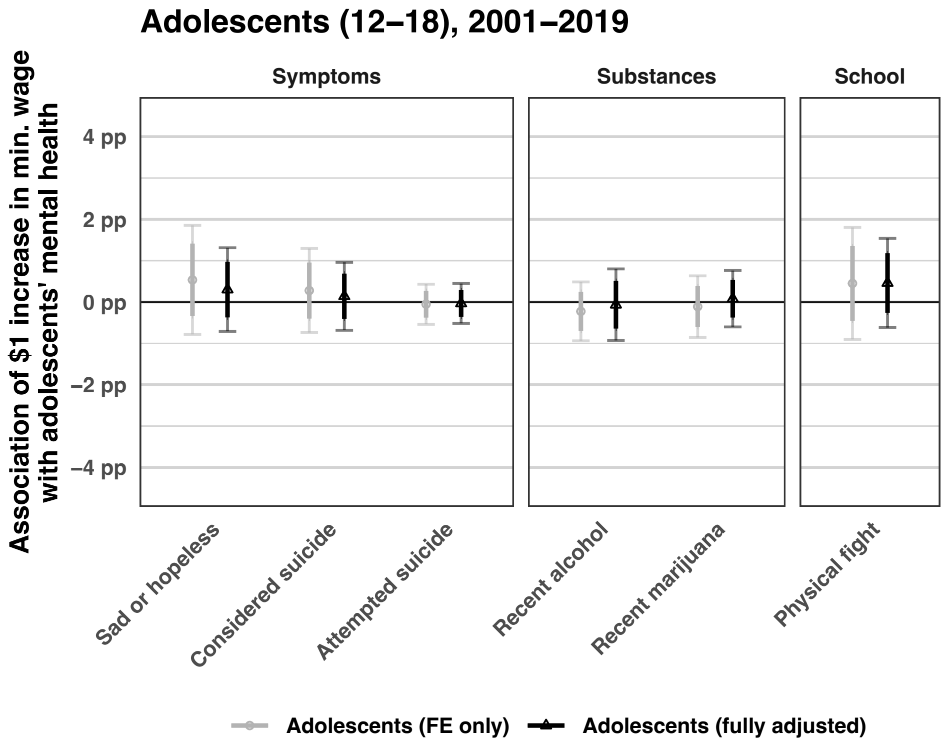

Figure A3. Main TWFE models with Bonferroni corrections for the YRBSS.

Notes: Re-estimation of the main OLS TWFE models with Bonferroni corrections for 15 outcomes. The thick lines provide the uncorrected 95% CIs (i.e. with critical values of 1.96), while the thin ones provide the Bonferroni-corrected 99.7% CIs (i.e. critical values of 2.94). All models include state and age-by-year fixed effects, while fully adjusted models add individual- and state-level covariates per **Table A2**. SEs are clustered at the state level. N = 922,636 to 1,218,309.

TWFE Sub-Population Analyses

We tested the association between the minimum wage and the mental health of several vulnerable sub-populations that were most likely to earn near the minimum wage (and, therefore, most likely to experience an improvement in their health after it was raised) (**Table A3**):

These sub-population analyses were formalized as interaction models:

$$Y_{ist} = \beta_1[(min.wage)_{st} * (group)_{ist}] + \beta_2(min.wage)_{st} + \beta_3(group)_{ist} +$$
$$\boldsymbol{\beta X_{ist}} + \boldsymbol{\beta Z_{st}} + \Delta_s + \tau_t + \varepsilon_{ist}$$

where a binary variable, $group_{ist}$, was defined for each sub-population of interest with inclusion = 0 and non-inclusion = 1. For example, Black and Hispanic/Latino children were coded as 0 and all other children who had complete information on race/ethnicity were coded as 1. As a result, β_3 provided the desired association for the sub-population of interest, i.e. Black and Hispanic/Latino children. We repeated the same procedure for all sub-populations listed above.

We provide these subgroup analyses in **Figures A4** and **A5**. There is little evidence of meaningful improvements for any outcome or any vulnerable group. Occasionally, there are 95% CIs that are statistically significant from zero, but these models (1) do not show a consistent pattern within outcomes, e.g. raising the minimum wage is negatively associated with rates of ADD/ADHD for low-income children in the NSCH but no other sub-populations; (2) do not show a consistent direction within sub-populations, e.g. for low-income children, raising the minimum wage is negatively associated with rates of ADD/ADHD yet positively associated with rates of depression; (3) do not use a causal design; and (4) are typically no longer significant under the 99.7% CIs. As a result, our interpretation of these models is that they are generally null.

Table A3. List of sub-population analyses for TWFE models.

Survey	Sub-population	Reference group
NSCH	Less than 200 FPL%	Households earning ≥200% FPL
NSCH	Adults with high school or less *That is, all households for which no adult completed more than H.S.*	All other adult education levels
NSCH	Black or Hispanic/Latino	All other races/ethnicities
NSCH	First- or second-generation	Third- or higher-generation children
NSCH	Adolescents, age 13–17	Children aged 3–12
YRBSS*	Black or Hispanic/Latino	All other races/ethnicities

Notes: *The YRBSS has fewer available demographic and socioeconomic characteristics than the NSCH, so we cannot replicate most of the sub-population analyses with the YRBSS.

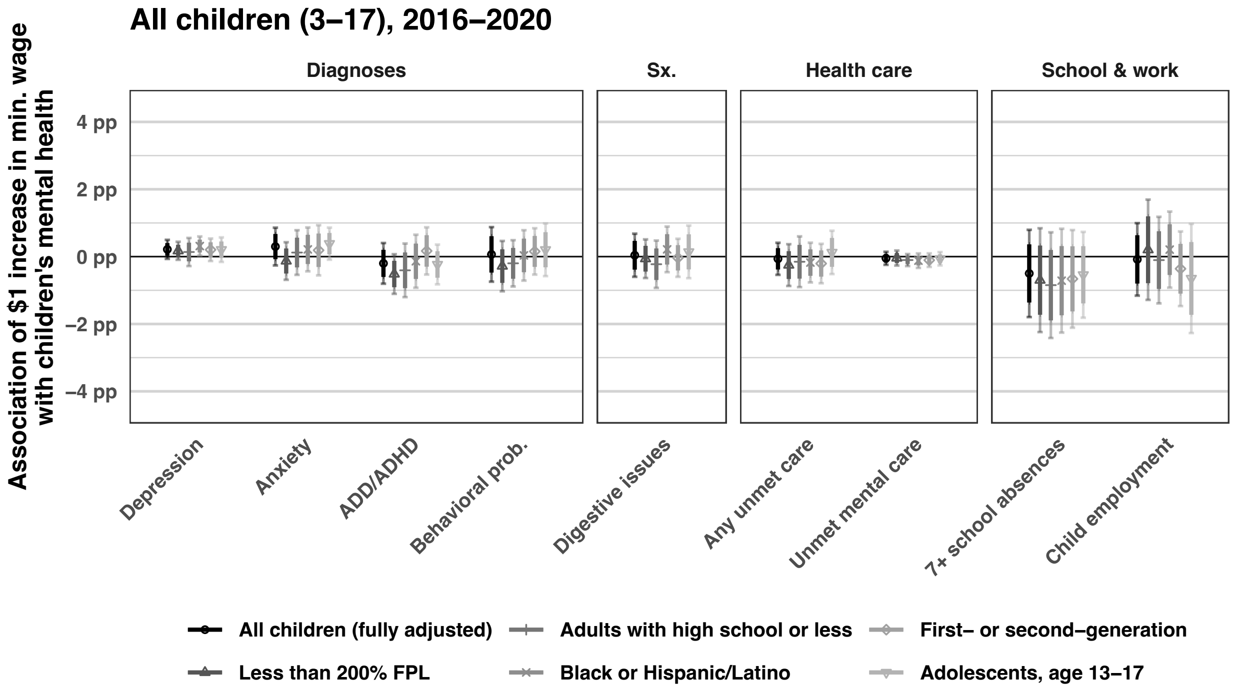

Figure A4. TWFE models for vulnerable sub-populations in the NSCH.

Notes: Based on OLS TWFE models that include interaction terms for the indicated sub-populations. All models are adjusted for state and year fixed effects, as well as individual- and state-level covariates per **Table A2**. SEs are clustered at the state level. 95% CIs (thick) and 99.7% CIs for Bonferroni corrections (thin) are provided. N = 114,163 to 141,094.

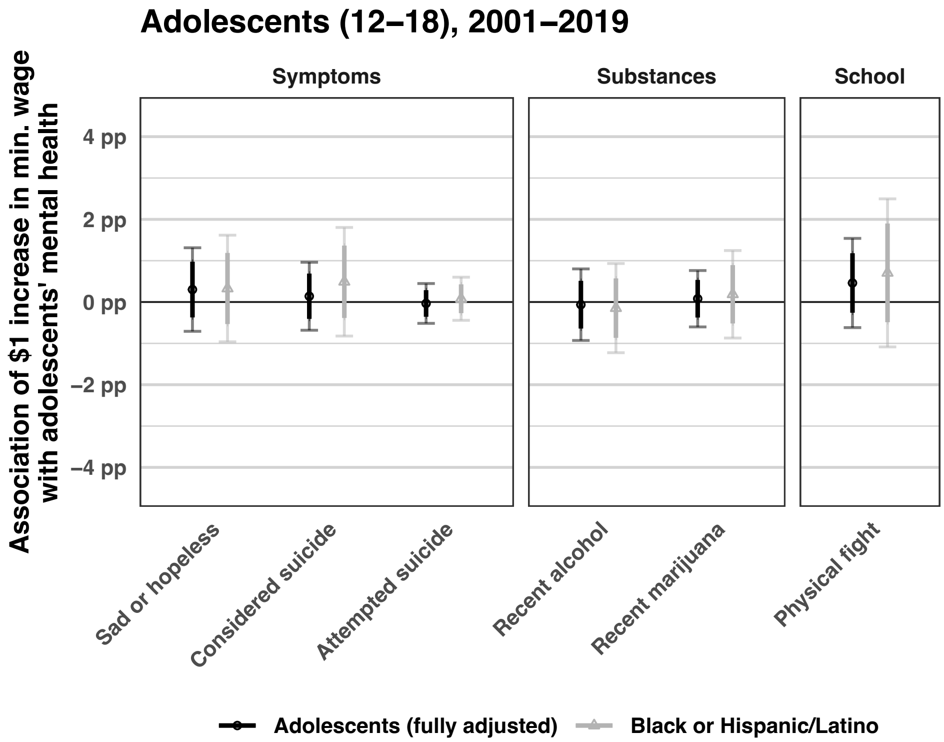

Figure A5. TWFE models for a vulnerable sub-population in the YRBSS.

Notes: Based on OLS TWFE models that include interaction terms for the indicated sub-population. All models are adjusted for state and age-by-year fixed effects, as well as individual- and state-level covariates per **Table A2**. SEs are clustered at the state level. 95% CIs (thick) and 99.7% CIs for Bonferroni corrections (thin) are provided. N = 922,636 to 1,218,309.

TWFE Robustness Analyses

We also examined the robustness of our analyses to several alternative specifications: (1) inflation-adjusted minimum wages (in 2020 dollars), in case only changes in a household's real income are associated with improved mental health; (2) wages lagged by 1 year, in case gains in mental health take time to manifest; and (3) estimations using binomial logistic regression, which provide the odds ratio for each outcome given a $1 increase in the minimum wage (the logistic regression models were estimated using the "survey" package in R). For all three, the associations are virtually the same as in the main, fully adjusted models (**Figures A6** to **A9**).

Next, we drew on the example of Wehby and colleagues, who found that children exposed to a higher minimum wage earlier in life had better physical health later.[2] The same could be true for mental health. For example, a family's wage in past years may have granted them access to structural opportunities, such as higher-quality schools or neighborhoods, that had a lasting impact on their child's mental health. Or it could be that families were better able to accumulate wealth in the past that they could later tap into when their child's well-being was threatened.

As such, we tested the average minimum wage to which a child was exposed throughout their life as a predictor in our models. To construct this variable, we averaged the minimum wage in a child's state of residence for all ages from 0 until when surveyed. Given the absence of data on a household's movement in the NSCH and YRBSS, we assumed that a child remained in the same state since birth. In reality, 2–3% of households move between states in a typical year, per the American Community Survey, so our lifetime minimum wage variable is measured with some error. Even so, it allows us to approximate the association between cumulative exposure to a state's minimum wages and a child's mental health later in life. These models are also adjusted for the same individual- and state-level covariates as the main models. They are presented in **Figures A10** and **A11**. These models are less well-specified than the main ones, so we cannot rule out meaningful effect sizes. Even so, they provide little evidence that higher minimum wages, even when sustained throughout a child's life, are associated with better mental health.

Lastly, we present models that use the nested clustered SEs recommended by the NSCH and YRBSS for estimating the prevalence of conditions and behaviors in the population, rather than clustering at the state level (**Figures A12** and **A13**). In the case of the NSCH, the alternate standard errors nest the survey's sampling strata within each state. Meanwhile, for the YRBSS, the alternate errors nest the survey's sampling strata with the state-based primary sampling units. These alternative constructions reflect the sampling approaches of the two surveys.

Given that our treatment, i.e. the minimum wage, is set by each state, clustering at the state level would traditionally be considered appropriate for TWFE and difference-in-differences analyses. Recent econometric evidence suggests that typical estimators for cluster-robust standard errors are overly conservative when a non-negligible fraction of clusters (in our case, states) in the population are sampled.[3] Such is the case here since we observe all states (plus D.C.). As such, the state-clustered errors may, in principle, overstate the true uncertainty in the association between the minimum wage and children's mental health. Meanwhile, the nested errors inflate the true number of clusters relative to the number of units with varying treatment statuses; as such, they may, in principle, understate the true uncertainty. Even so, the two approaches produce substantively similar estimates of uncertainty for our outcomes (**Figures A12** and **A13**).

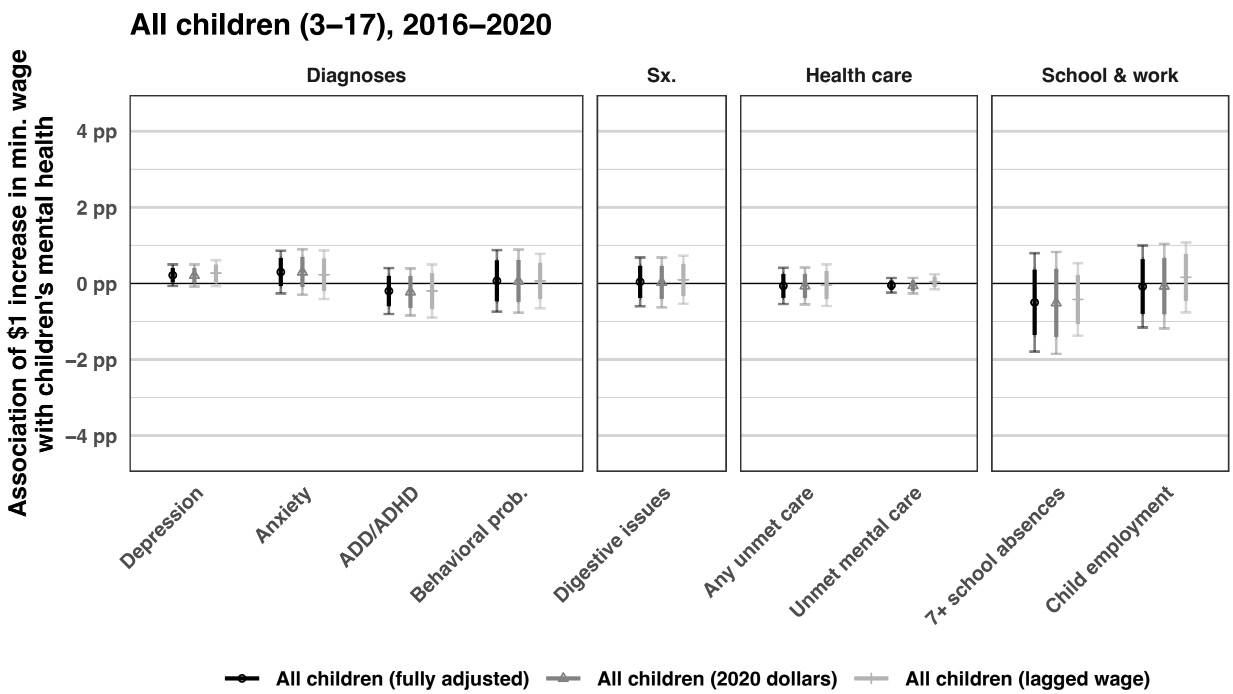

Figure A6. TWFE models with alternative specifications for the NSCH.

Notes: Based on OLS TWFE models using (1) the state's effective minimum wage adjusted for inflation in 2020 dollars and (2) the state's minimum wage lagged by one year, compared to (3) the main TWFE models. All models are adjusted for individual- and state-level covariates per **Table A2**, as well as state and year fixed effects. SEs are clustered at the state level. 95% CIs (thick) and 99.7% CIs for Bonferroni corrections (thin) are provided. N = 114,163 to 141,094.

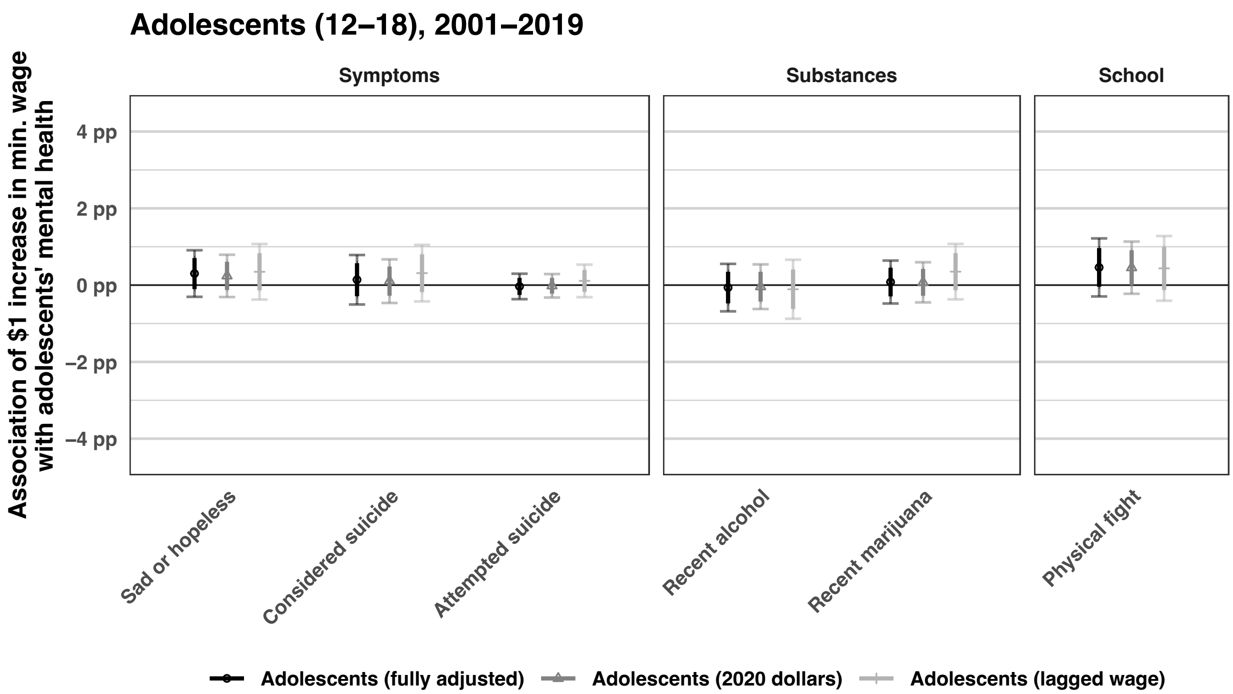

Figure A7. TWFE models with alternative specifications for the YRBSS.

Notes: Based on OLS TWFE models using (1) the state's effective minimum wage adjusted for inflation in 2020 dollars and (2) the state's minimum wage lagged by one year, compared to (3) the main TWFE models. All models are adjusted for individual- and state-level covariates per **Table A2**, as well as state and age-by-year FEs. SEs are clustered at the state level. 95% CIs (thick) and 99.7% CIs for Bonferroni corrections (thin) are provided. N = 922,636 to 1,218,309.

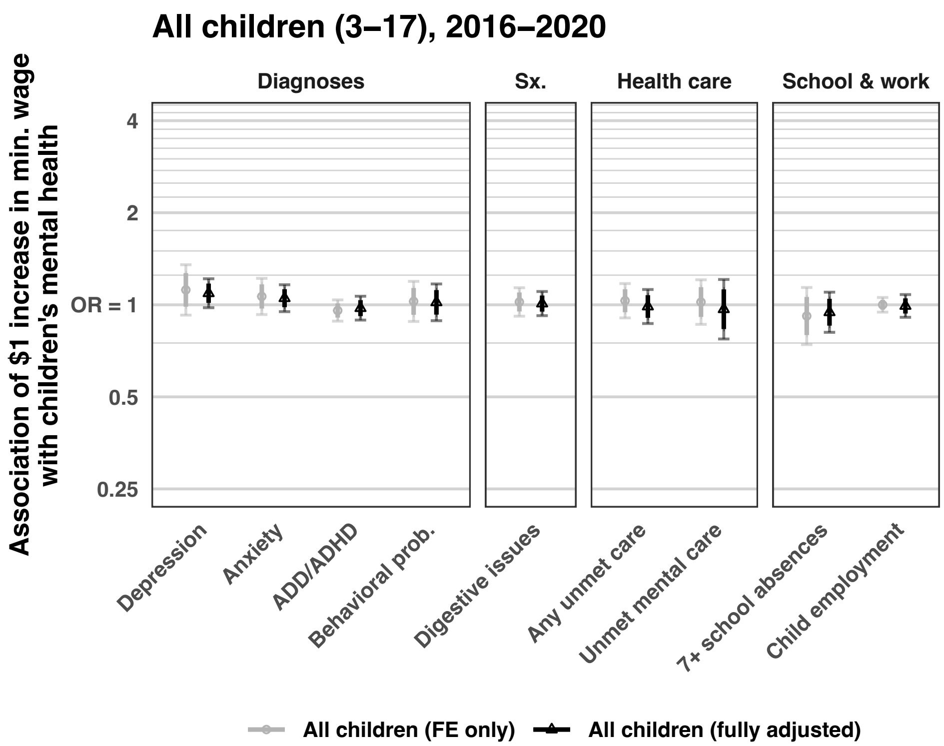

Figure A8. TWFE models using logistic regression for the NSCH.

Notes: Re-estimation of the main TWFE models with binomial logistic regression in the "survey" package in R. All models include state and year FEs; fully adjusted models add individual- and state-level covariates per **Table A2**. SEs are clustered at the state level. 95% CIs (thick) and 99.7% CIs for Bonferroni corrections (thin) are provided. N = 114,163 to 141,094.

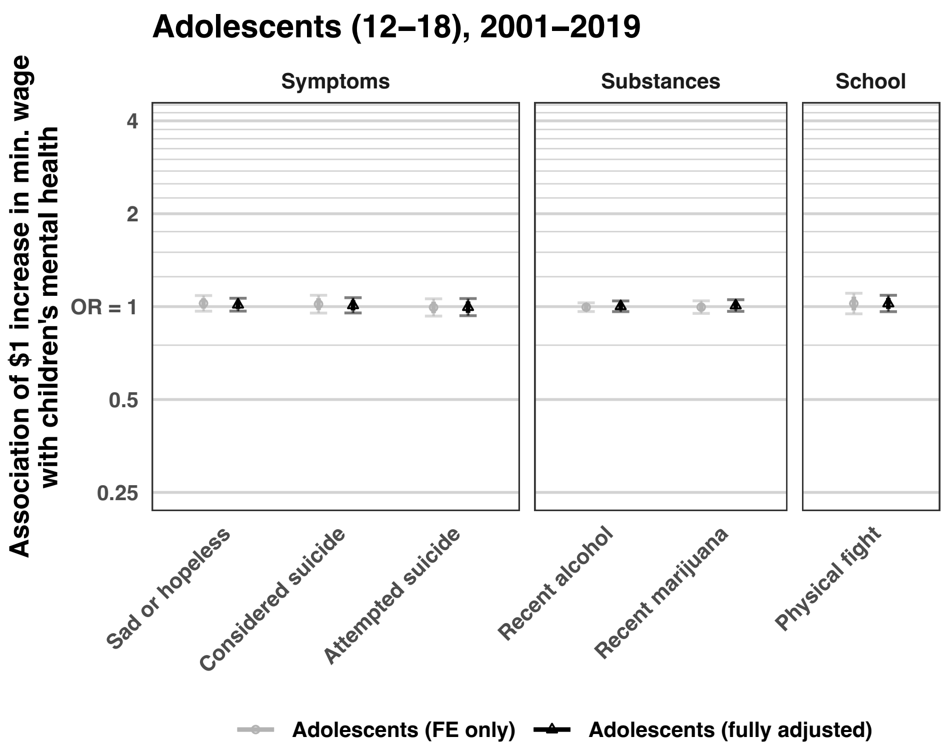

Figure A9. TWFE models using logistic regression for the YRBSS.

Notes: Re-estimation of the main TWFE models with binomial logistic regression in the "survey" package in R. All models include state and age-by-year FEs; fully adjusted models add individual- and state-level covariates per **Table A2**. SEs are clustered at the state level. 95% CIs (thick) and 99.7% CIs for Bonferroni corrections (thin) are provided. N = 922,636 to 1,218,309.

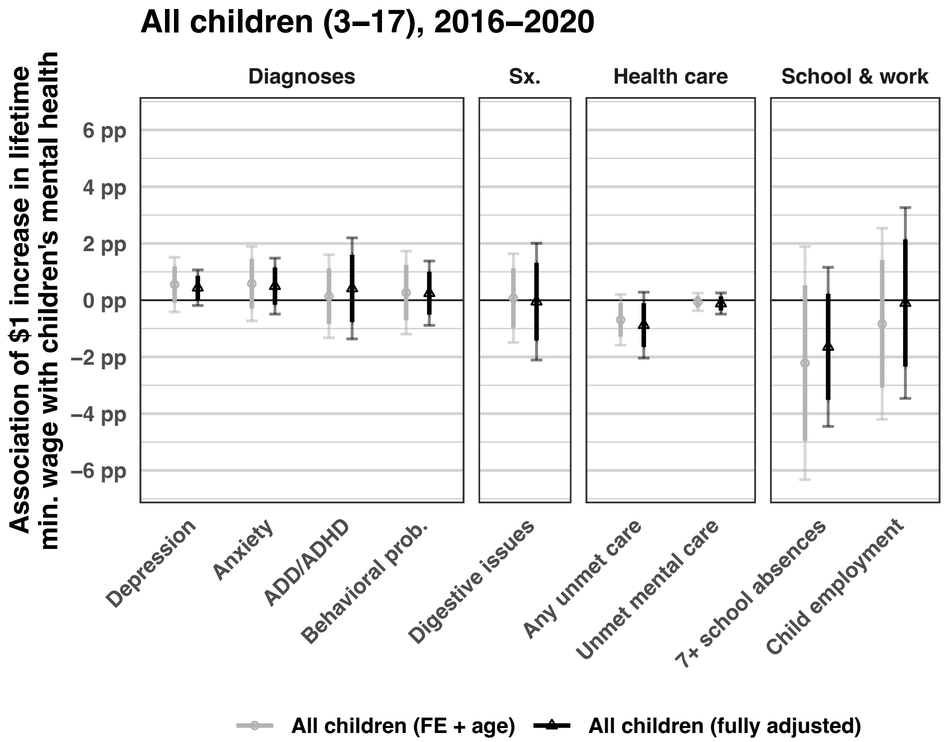

Figure A10. TWFE models using lifetime minimum wages for the NSCH.

Notes: Based on OLS TWFE models using the average minimum wage to which a child was exposed throughout their life. All models include state and year FEs; fully adjusted models add individual- and state-level covariates per **Table A2**. SEs are clustered at the state level. 95% CIs (thick) and 99.7% CIs for Bonferroni corrections (thin) are provided. N = 114,163 to 141,094.

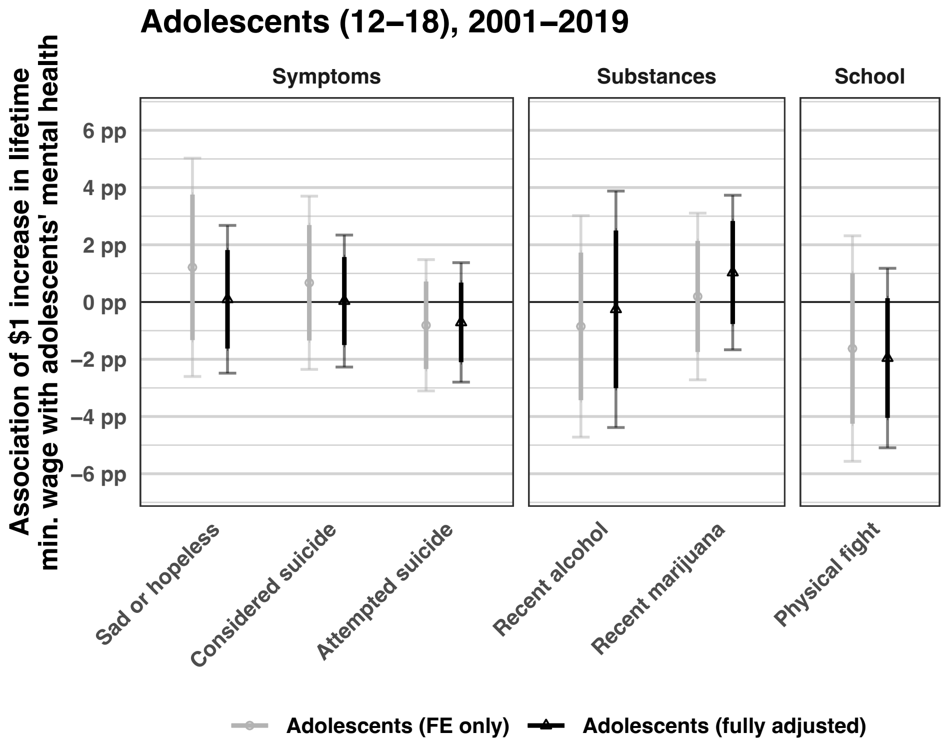

Figure A11. TWFE models using lifetime minimum wages for the YRBSS.

Notes: Based on OLS TWFE models using the average minimum wage to which a child was exposed throughout their life. All models include state and age-by-year FEs; fully adjusted models add individual- and state-level covariates per **Table A2**. SEs are clustered at the state level. 95% CIs (thick) and 99.7% CIs for Bonferroni corrections (thin) are provided. N = 922,636 to 1,218,309.

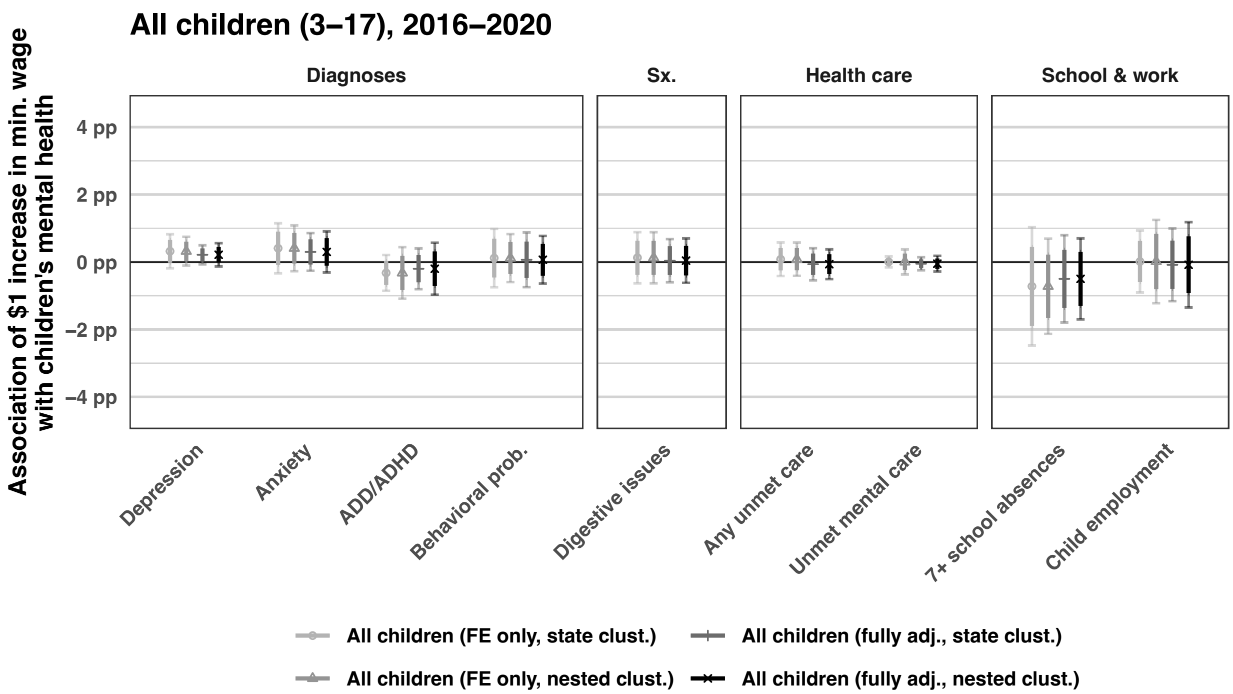

Figure A12. TWFE models using nested clusters for the NSCH.

Notes: Re-estimation of the main TWFE models with SEs clustered using the NSCH's nested design. State-clustered SEs are included for comparison. All models include state and year FEs; fully adjusted models add individual- and state-level covariates per **Table A2**. 95% CIs (thick) and 99.7% CIs for Bonferroni corrections (thin) are provided. N = 114,163 to 141,094.

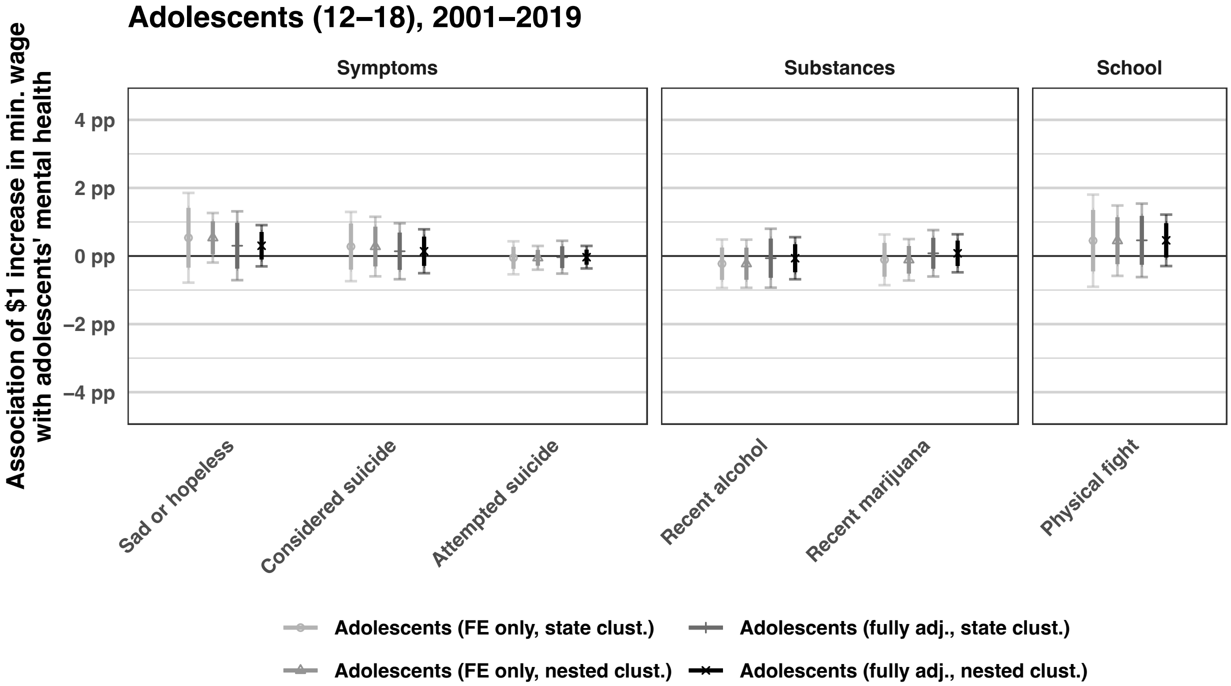

Figure A13. TWFE models using nested clusters for the YRBSS.

Notes: Re-estimation of the main TWFE models with SEs clustered using the YRBSS's nested design. State-clustered SEs are included for comparison. All models include state and age-by-year FEs; fully adjusted models add individual- and state-level covariates per **Table A2**. 95% CIs (thick) and 99.7% CIs for Bonferroni corrections (thin) are provided. N = 922,636 to 1,218,309.

Difference-in-Differences Specifications

Recent advancements in the econometrics literature on TWFE models have highlighted the potential biases in this approach when units adopt policies at different times and experience dynamic treatment effects over time.[4–6] Consequently, our standard TWFE models may not provide direct causal interpretations. Given that a causal interpretation is more valuable for policy makers and public health professionals, we also specify difference-in-differences models to evaluate whether raising the state minimum wage causally affects children's mental health.

For our causal analyses, we focused on the years following the last major increase in the federal minimum wage, i.e. post–2010. We used the YRBSS outcomes since the YRBSS provided a sufficiently long number of follow-up years. To define a set of treatment states with suitable pre- and post-periods, we coded as treated the 10 states that raised their minimum wages from the federal minimum of \$7.25 between the 2013 and 2015 waves of the YRBSS (**Figure A14, panel A**). This choice provided us with two pre-periods to evaluate parallel pre-trends and 3 post-periods to evaluate for long-run effects. The 21 states that remained at the federal minimum wage of \$7.25 from 2011 to 2019 served as control states. Note that Indiana also remained at the federal minimum but did not field a YRBSS survey. All other states were excluded.

During this period, treated states implemented a range of minimum wage increases, as shown in **Figure A14, panel B**. Treated adolescents were exposed to a weighted mean wage of \$9.61 in the post-period, or a \$2.36 increase over baseline. Consequently, our difference-in-differences models estimate the average causal effect of a \$2.36 increase in the minimum wage on the mental health of treated adolescents, rather than the \$1 increase in the TWFE models.

The main difference-in-differences models were specified as follows:

$$Y_{ist} = \beta_1(treated)_s + \beta_2(post2013)_t + \beta_3(treated \times post2013)_{st} +$$
$$\boldsymbol{\beta X_{ist}} + \boldsymbol{\beta Z_{st}} + \Delta_s + \tau_t + \varepsilon_{ist}$$

where Y_{ist} is the mental health outcome for individual *i* in state *s* in year *t*; $(treated)_s$ is an indicator for whether a state was in the treatment group (coded as 1) or control group (0); $(post2013)_t$ is an indicator for whether an observation is in the pre-treatment period (2011 or 2013, coded as 0) or post-period (2015 onward, 1); the coefficient on the interaction term, β_3, estimates the difference-in-difference, or the average treatment effect on treated adolescents. X_{ist} is a vector of individual-level controls (per **Table A2**); Z_{st} is a vector of time-variant state-level policies; Δ_s is the time-invariant state fixed effect; τ_t is the year (or age-by-year) fixed effect; and ε_{ist} is the error.

We also specify event studies models, which are akin to difference-in-differences but allow the treatment effect to vary by year. As a result, they allow us to confirm parallel pre-trends and evaluate how the treatment effect changes in over time. Treated adolescents were exposed to a mean minimum wage of \$8.39 (or \$1.14 over baseline) in 2015, \$9.23 (or \$1.98) in 2017, and \$10.88 (or \$3.63) in 2019 (**Figure A15**). Because the mean treatment continued to grow during this period, we might also expect the effect on mental health to grow over time.

The event studies were estimated as follows:

$$Y_{ist} = \beta_1(treated)_s + \boldsymbol{\beta}(year)_t + \boldsymbol{\beta}(treated \times year)_{st} + \boldsymbol{\beta X_{ist}} + \boldsymbol{\beta Z_{st}} + \Delta_s + \tau_t + \varepsilon_{ist}$$

where we have a vector of coefficients of interest, one for the treatment effect in each year.

Together, the difference-in-differences and event study models allow us to rigorously evaluate the causal effect of raising the minimum wage on the mental health of adolescents. All use the YRBSS weights and cluster SEs at the state level. We provide 95% CIs as well as Bonferroni-corrected 99.2% CIs (since we only consider 6 outcomes, 0.05/6 = 0.0083, with corresponding critical values of 2.64). All were estimated by OLS in the "lfe" package (v. 2.8) in R.

The main difference-in-differences models are presented in **Table A4**, while the main event studies are presented in **Figure A16**. They provide little to no evidence that raising a state's minimum wage by a weighted mean of \$2.36 improved adolescents' mental health from 2011–2019. If anything, they suggest that some outcomes worsened. Using the 95% CIs, we can rule out improvements greater than 1 pp for all outcomes except recent alcohol use, for which we can rule out effects greater than 2 pp. The event studies suggest that the effects do not accumulate or phase in over time as we might expect since the minimum wages of treated states continued to rise during the post-period. The event studies also reduce concerns about non-parallel pre-trends, except possibly for getting in physical fights. We also reproduce these models using the YRBSS's nested clusters; they appear similar to the state-clustered SEs (**Figure A17**).

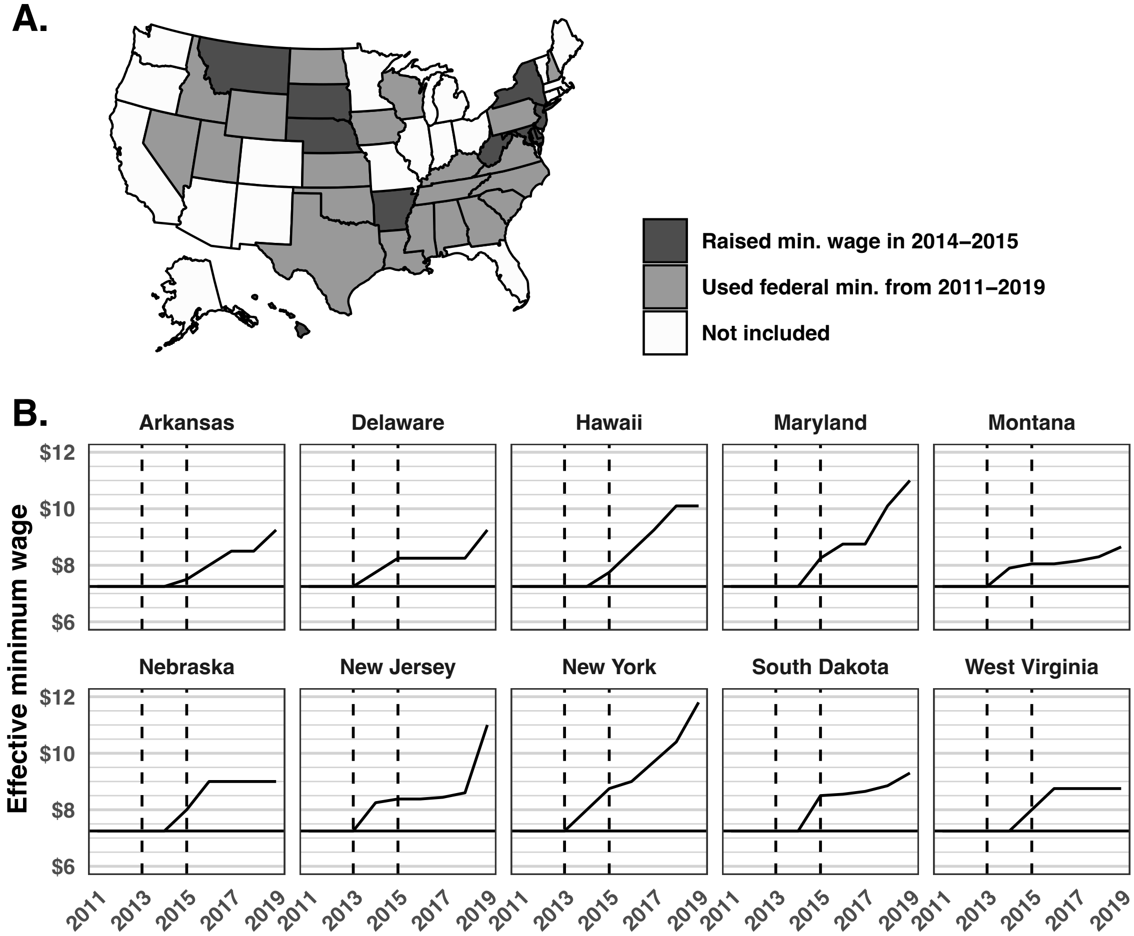

Figure A14. Treatment and control states for difference-in-differences models.

Notes: (A.) States that started raising their minimum wage above the federal minimum in 2014 or 2015 serve as treatment states, while those that remained at the federal minimum serve as controls. (B.) Effective minimum wages in treatment states, per Bureau of Labor Statistics data.

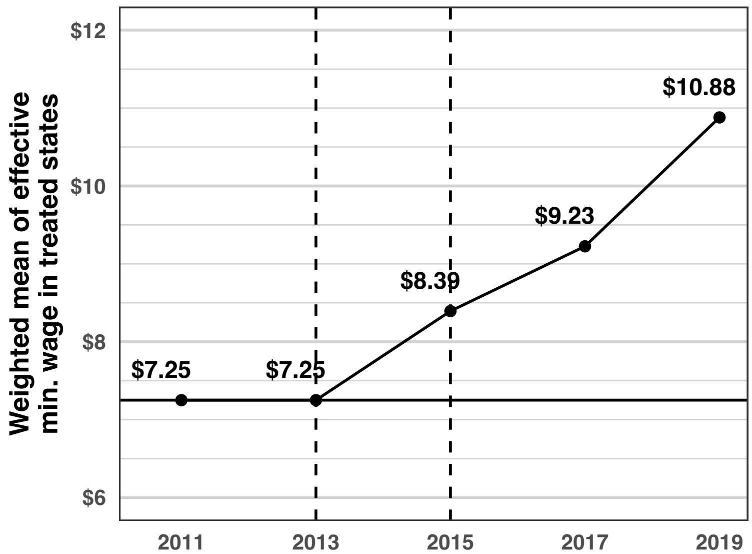

Figure A15. Weighted mean of minimum wage in treatment states.

Notes: These estimates provide the effective minimum wage to which the mean treated adolescent was exposed using the YRBSS weights. Based on Bureau of Labor Statistics data.

Table A4. Difference-in-difference models for the average treatment effect of raising the minimum wage on treated adolescents' mental health using the YRBSS from 2011–2019.

	Sad or hopeless		Considered suicide	
	FE only	**Fully adj.**	**FE only**	**Fully adj.**
Effect of raise in wage	1.5	1.6	0.6	1.0
95% CIs	[–0.5, 3.4]	[0.1, 3.2]	[–0.8, 1.9]	[0.0, 2.0]
99.2% CIs	[–1.2, 4.1]	[–0.5, 3.8]	[–1.3, 2.4]	[–0.3, 2.4]
Demographic controls	No	Yes	No	Yes
State policy controls	No	Yes	No	Yes
State and age-by-year FEs	Yes	Yes	Yes	Yes
Cluster-robust SEs	State	State	State	State
Number of adolescents	552,169	552,169	553,694	553,694
Adjusted R2	0.009	0.046	0.004	0.020

	Attempted suicide		Recent alcohol	
	FE only	**Fully adj.**	**FE only**	**Fully adj.**
Effect of raise in wage	0.3	0.9	–0.3	–0.2
95% CIs	[–1.3, 2.0]	[–0.1, 1.9]	[–2.2, 1.6]	[–1.8, 1.4]
99.2% CIs	[–2.0, 2.7]	[–0.5, 2.2]	[–2.9, 2.4]	[–2.4, 2.0]
Demographic controls	No	Yes	No	Yes
State policy controls	No	Yes	No	Yes
State and age-by-year FEs	Yes	Yes	Yes	Yes
Cluster-robust SEs	State	State	State	State
Number of adolescents	314,791	314,791	512,373	512,373
Adjusted R2	0.005	0.014	0.040	0.055

	Recent marijuana		Physical fight	
	FE only	**Fully adj.**	**FE only**	**Fully adj.**
Effect of raise in wage	0.1	0.1	–0.3	–0.2
95% CIs	[–0.7, 0.9]	[–0.7, 0.9]	[–0.8, 2.2]	[–0.6, 2.0]
99.2% CIs	[–1.1, 1.3]	[–1.0, 1.2]	[–1.4, 2.7]	[–1.1, 2.4]
Demographic controls	No	Yes	No	Yes
State policy controls	No	Yes	No	Yes
State and age-by-year FEs	Yes	Yes	Yes	Yes
Cluster-robust SEs	State	State	State	State
Number of adolescents	539,241	539,241	311,828	311,828
Adjusted R2	0.018	0.024	0.011	0.046

Notes: The coefficients provide the effect of raising the minimum wage in percentage points on adolescents' mental health from 2011–2019. Based on OLS difference-in-difference models using the states indicated in **Figure A14** and the YRBSS outcomes. All models include the indicated adjustments per **Table A2**. 95% CIs and 99.2% CIs for Bonferroni corrections are provided.

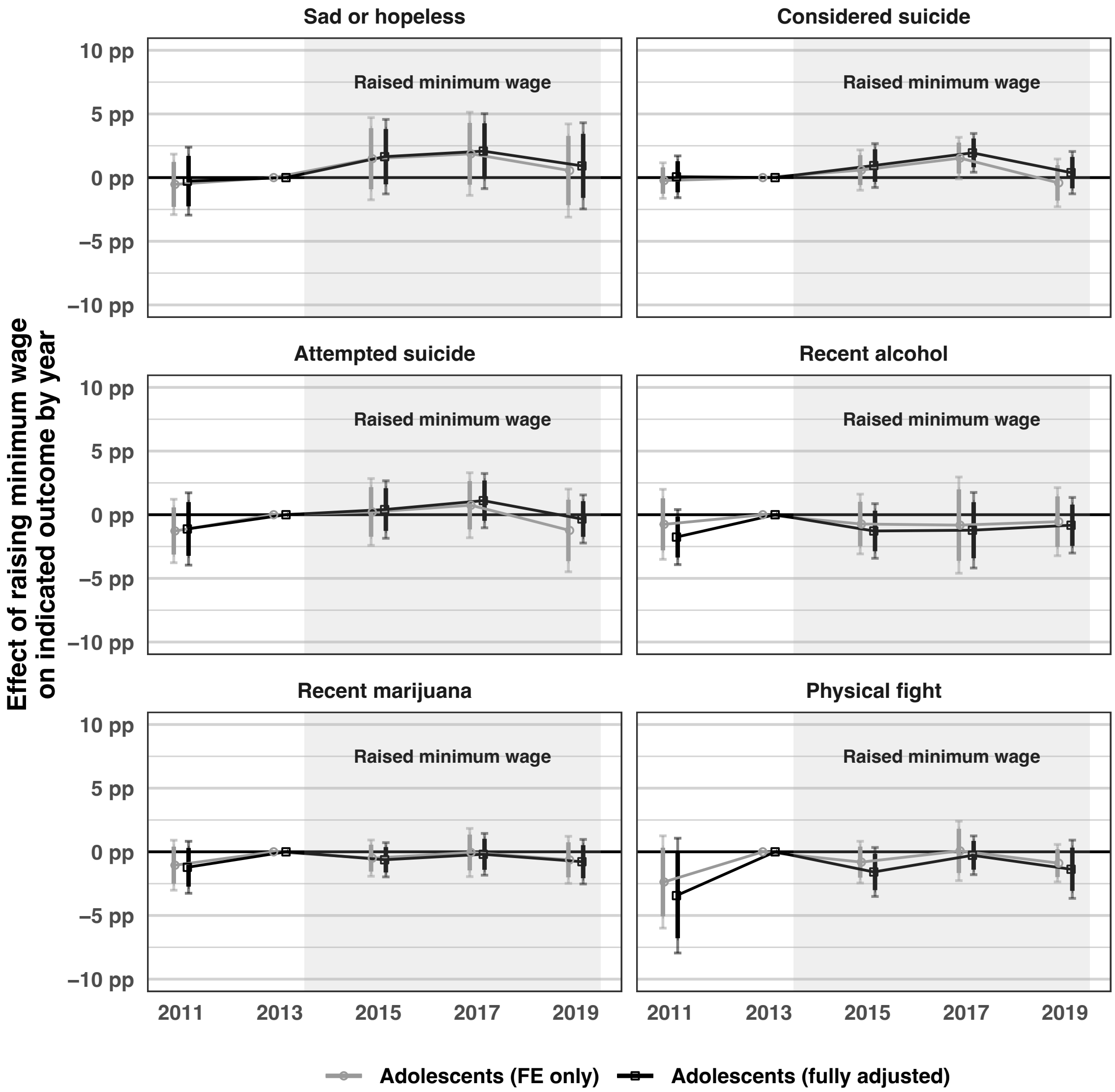

Figure A16. Main event studies using the YRBSS from 2011–2019.

Notes: Each coefficient provides the effect of raising the minimum wage in the indicated year. Based on OLS event study models using the cohort of states that raised their minimum wages above the federal minimum in 2014 or 2015, compared to those that used the federal minimum for the entire period. All models include state and age-by-year FEs; fully adjusted models add individual- and state-level covariates per **Table A2**. SEs are clustered at the state level. 95% CIs (thick) and 99.2% CIs for Bonferroni corrections (thin) are provided. N = 311,828 to 553,694.

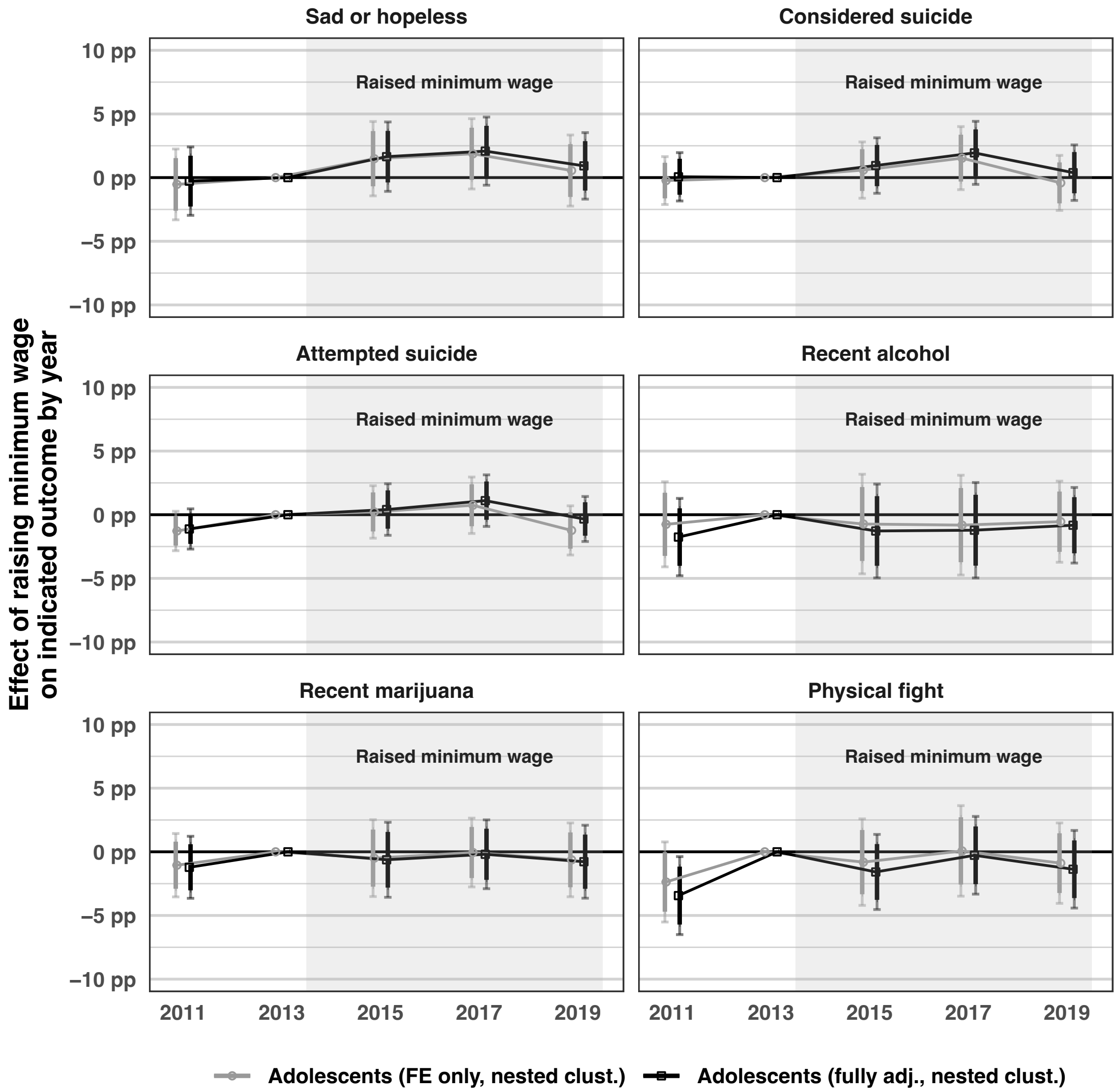

Figure A17. Event studies using nested clusters for the YRBSS.

Notes: Re-estimation of the main event studies with SEs clustered using the YRBSS's nested design. See **Figure A16** for the state-clustered SEs. All models include state and age-by-year FEs; fully adjusted models add individual- and state-level covariates per **Table A2**. 95% CIs (thick) and 99.2% CIs for Bonferroni corrections (thin) are provided. N = 311,828 to 553,694.

Event Studies with Strictly Balanced Panel

Since not all states field the YRBSS in all years, one concern might be that the main event studies are biased by an imbalanced panel. That is, the coefficients rely on slightly different combinations of states depending on the year, which might affect our inferences. To reduce this concern, we reproduce the models on a strictly balanced panel of 7 treated states (i.e. AR, HI, MD, MT, NE, NY, and WV) and 9 control states (i.e. ID, KY, NC, ND, NH, OK, SC, TN, and VA) (**Figure A18**). They may suggest that raising the minimum wage caused rates of alcohol use to decline by 2.5 pp in 2017 and 2019. However, other outcomes (i.e. sad or hopeless and suicide attempts) appear to have worsened in some years. As a result, these models are inconsistent with widespread improvements in adolescents' mental health, much like the main event studies.

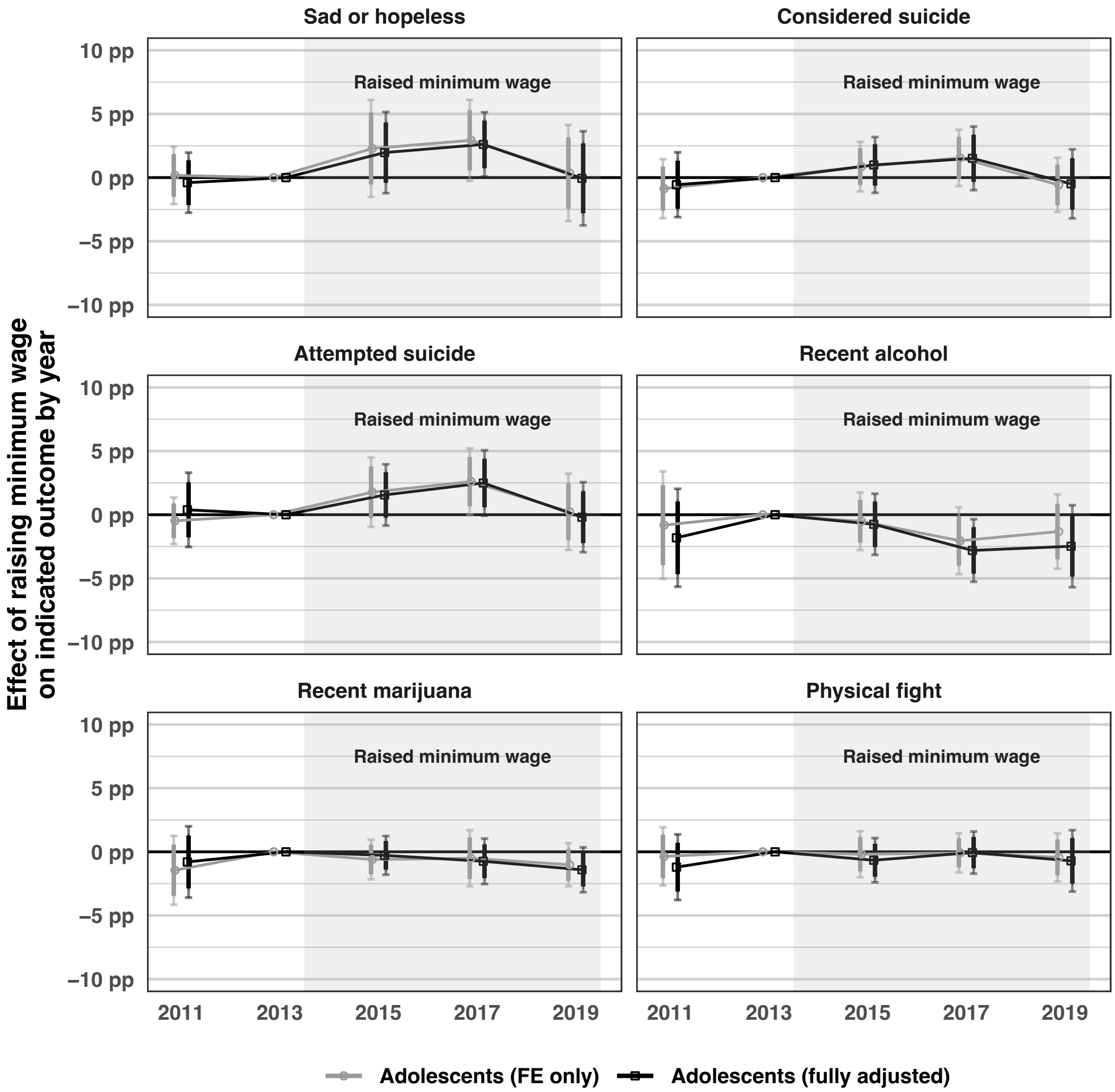

Figure A18. Event studies using a strictly balanced panel for the YRBSS.

Notes: Re-estimation of the main event studies using a strictly balanced panel of 7 treated states (i.e. AR, HI, MD, MT, NE, NY, and WV) and 9 control states (i.e. ID, KY, NC, ND, NH, OK, SC, TN, and VA). All models include state and age-by-year FEs; fully adjusted models add individual- and state-level covariates per **Table A2**. SEs are clustered at the state level. 95% CIs (thick) and 99.2% CIs for Bonferroni corrections (thin) are provided. N = 214,355 to 445,969.

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