

The Minimum Wage and Children’s Mental Health

Online Appendix

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Section A1. State Participation in the YRBSS

Not all states participate in the YRBSS in all years. The following table presents the unweighted number of adolescents who were included in our analyses for each state-year:

Table A1. Unweighted number of respondents to the YRBSS by state and year.

	2001	2003	2005	2007	2009	2011	2013	2015	2017	2019
AK	0	1438	0	1268	1217	1279	1183	1343	1279	1799
AL	1551	1064	1026	0	1457	1336	1518	1510	0	1971
AR	1670	0	1502	1563	1627	1327	1491	2746	1593	1935
AZ	0	3369	3216	2929	2485	2747	1566	2478	2056	1859
CA	0	0	0	0	0	0	0	1873	1708	1298
CO	0	0	1475	0	1491	1424	0	0	1427	1288
CT	0	0	2206	1996	2319	2000	2307	2315	2331	1981
DE	2862	2969	2633	2357	2256	2187	2584	2636	2801	0
FL	4064	3949	4444	4353	5365	5977	5831	6081	5919	5527
GA	0	2046	1728	2393	1826	1897	1907	0	0	4347
HI	0	0	1626	1148	1455	4172	4465	5773	5686	5527
IA	0	0	1350	1419	0	1513	0	0	1635	1532
ID	1687	1702	1426	1384	2102	1659	1838	1705	1774	1174
IL	0	0	0	2362	2932	3507	3148	3133	4745	2989
KS	0	0	1633	1692	1998	1833	1894	0	2337	1360
KY	0	1562	3231	3482	1726	1669	1587	2465	1932	1920
LA	0	0	0	1298	1002	1115	1062	0	1186	1241
MD	0	0	1397	1485	1590	2791	51137	52841	48392	38973
ME	1320	1634	1325	1267	8444	9074	8341	9112	9003	7995
MI	3521	3374	3171	3425	3314	4082	4137	4661	1568	4365
MO	1632	1532	1861	1520	1596	0	1556	1431	1759	1156
MS	1790	1471	0	1563	1763	1751	1559	2038	0	1693
MT	2622	2678	2987	3845	1785	4020	4744	4308	4596	3676
NC	2520	2521	3821	3397	5549	2215	1791	5886	3022	2907
ND	1580	1649	1710	1721	1767	1862	1919	2064	2064	1975
NE	0	2913	3706	0	0	2641	1747	1633	1381	1275
NH	0	1298	1249	1581	1450	1359	1589	14305	11552	13084
NJ	2102	0	1482	0	1724	1617	1661	0	0	1360

	2001	2003	2005	2007	2009	2011	2013	2015	2017	2019
NM	0	0	5415	2558	4890	5685	5325	8170	5650	7447
NV	1439	1947	1528	1729	2017	0	2069	1393	1607	1359
NY	0	9077	9456	12768	14134	12517	10026	10109	10674	10159
OK	0	1366	1688	2562	1397	1136	1465	1559	1583	1937
PA	0	0	0	0	2037	0	0	2795	3599	2255
RI	1361	1775	2315	2132	3106	3814	2357	3309	2128	1535
SC	0	0	1281	1205	1070	1437	1552	1309	1425	1153
SD	1596	1803	1567	1577	2121	1502	1272	1257	0	1385
TN	0	1919	1529	2019	2175	2583	1847	3970	1975	2148
TX	6974	0	4098	3116	3435	4054	3086	0	2027	1954
UT	1042	1359	1437	1898	1543	1656	2118	0	1772	1476
VA	0	0	0	0	0	1400	6641	4309	3565	4531
VT	6965	5928	6996	5743	8188	8267	0	20149	19642	18270
WI	2091	2100	2352	2056	2392	2959	2776	0	1993	1786
WV	0	1719	1317	1353	1603	2119	1753	1567	1480	1342
WY	2684	1507	2455	2174	2802	2438	2924	2317	0	0

Section A2. Coding of Outcome Variables

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

Table A2. 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	1 if K2Q32B = 1 Otherwise, 0 if K2Q32B = 2 or if K2Q32A = 1 or 2
		Variable name: K2Q32B "If yes, does this child CURRENTLY have the condition?" 1 = Yes 2 = No Skip logic: Skip if K2Q32A=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	<p>Variable name: K2Q33A</p> <p>“Has a doctor or other health care provider EVER told you that this child has?...Anxiety Problems?”</p> <p>1 = Yes</p> <p>2 = No</p> <p>Variable name: K2Q33B</p> <p>“If yes, does this child CURRENTLY have the condition?”</p> <p>1 = Yes</p> <p>2 = No</p> <p><i>Skip logic: Skip if K2Q33A=2</i></p>	<p>1 if K2Q33B = 1</p> <p>Otherwise,</p> <p>0 if K2Q33B = 2 or</p> <p>if K2Q33A = 1 or 2</p>

Survey	Outcome	Question wording	Coding
NSCH (All children)	ADD/ADHD	<p>Variable name: K2Q31A</p> <p>“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?”</p> <p>1 = Yes 2 = No</p> <p>Variable name: K2Q31B</p> <p>“If yes, does this child CURRENTLY have the condition?”</p> <p>1 = Yes 2 = No</p> <p><i>Skip logic: Skip if K2Q31A=2</i></p>	<p>1 if K2Q31B = 1</p> <p>Otherwise, 0 if K2Q31B = 2 or if K2Q31A = 1 or 2</p>

Survey	Outcome	Question wording	Coding
NSCH (All children)	Behavioral prob.	<p>Variable name: K2Q34A</p> <p>“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.”</p> <p>1 = Yes</p> <p>2 = No</p> <p>Variable name: K2Q34B</p> <p>“If yes, does this child CURRENTLY have the condition?”</p> <p>1 = Yes</p> <p>2 = No</p> <p><i>Skip logic: Skip if K2Q34A=2</i></p>	<p>1 if K2Q34B = 1</p> <p>Otherwise,</p> <p>0 if K2Q34B = 2 or if K2Q34A = 1 or 2</p>
NSCH (All children)	Digestive issues	<p>Variable name: STOMACH</p> <p>“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”</p> <p>1 = Yes</p> <p>2 = No</p>	<p>1 if STOMACH = 1</p> <p>Otherwise,</p> <p>0 if STOMACH = 2</p>

Survey	Outcome	Question wording	Coding
NSCH (All children)	Any unmet care	<p>Variable name: K4Q27</p> <p>“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.”</p> <p>1 = Yes 2 = No</p>	<p>1 if K4Q27 = 1</p> <p>Otherwise, 0 if K4Q27 = 2</p>
NSCH (All children)	Unmet mental care	<p>Variable name: K4Q27</p> <p>“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.”</p> <p>1 = Yes 2 = No</p> <p>Variable name: K4Q28X04</p> <p>“Which types of care was/were not received?...Mental Health Services”</p> <p>1 = selected 2 = not selected</p> <p><i>Skip logic: Skip if K4Q27=2</i></p>	<p>1 if K4Q28X04 = 1</p> <p>Otherwise, 0 if K4Q27 = 1 or 2</p>

Survey	Outcome	Question wording	Coding
NSCH (All children)	7+ school absences	<p>Variable name: K7Q02R_R</p> <p>"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."</p> <p>1 = No missed school days</p> <p>2 = 1 - 3 days</p> <p>3 = 4 - 6 days</p> <p>4 = 7 - 10 days</p> <p>5 = 11 or more days</p> <p>6 = This child was not enrolled in school</p> <p><i>Skip logic: If FORMTYPE in ('T2','T3'), i.e. ages 6–17</i></p>	<p>1 if K7Q02R_R = 4–5</p> <p>Otherwise,</p> <p>0 if K7Q02R_R = 1–3, 6</p>
NSCH (All children)	Employment	<p>Variable name: K7Q38</p> <p>"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?"</p> <p>1 = Yes</p> <p>2 = No</p> <p><i>Skip logic: If FORMTYPE in ('T2','T3'), i.e. ages 6–17</i></p>	<p>1 if K7Q38 = 1</p> <p>Otherwise,</p> <p>0 if K7Q48 = 2</p>

Survey	Outcome	Question wording	Coding
YRBSS (Adolescents)	Sad or hopeless	<p>Variable name: Q25</p> <p>“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?”</p> <p>A. Yes</p> <p>B. No</p>	<p>1 if Q25 = A (1)</p> <p>Otherwise,</p> <p>0 if Q25 = B (2)</p>
YRBSS (Adolescents)	Considered suicide	<p>Variable name: Q26</p> <p>“During the past 12 months, did you ever seriously consider attempting suicide?”</p> <p>A. Yes</p> <p>B. No</p>	<p>1 if Q26 = A (1)</p> <p>Otherwise,</p> <p>0 if Q26 = B (2)</p>
YRBSS (Adolescents)	Attempted suicide	<p>Variable name: Q28</p> <p>“During the past 12 months, how many times did you actually attempt suicide?”</p> <p>A. 0 times</p> <p>B. 1 time</p> <p>C. 2 or 3 times</p> <p>D. 4 or 5 times</p> <p>E. 6 or more times</p>	<p>1 if Q28 = B–E (2–5)</p> <p>Otherwise,</p> <p>0 if Q28 = A (1)</p>

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

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

Section A3. 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.

Section A4. 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.

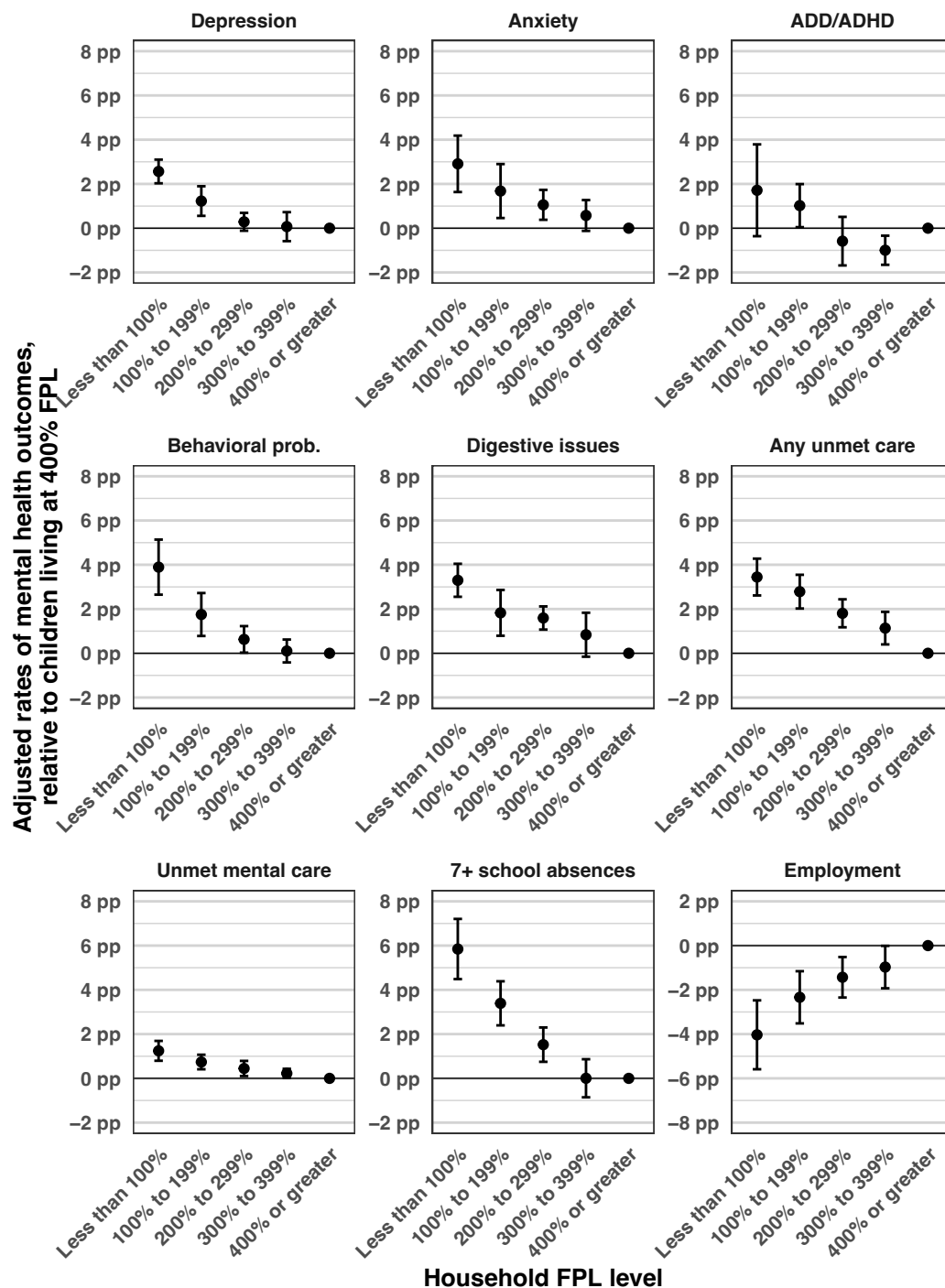


Figure A1. Adjusted mental health inequities by household income.

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 A3**, as well as state and year fixed effects. SEs are clustered at the state level. 95% CIs are provided.

Section A5. Two-Way Fixed Effects (TWFE) Specifications

The main TWFE models were specified as follows:

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

where Y_{ist} is the mental health outcome for individual i in state s in year t ; $(\text{min. wage})_{st}$ 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 A3**. Note that the YRBSS has fewer available covariates than the NSCH. These covariates were informed by several previous studies on the minimum wage and health (e.g.¹⁻⁴), as well as the evidence on inequities in mental health by demographics and socioeconomic status.⁵ The state policy controls, in particular, were drawn from two papers by Wehby and colleagues.^{3,4} Importantly, we exclude any individual- or policy-level controls that might be on the causal pathway from rising wages to mental health, including household income, unemployment rates, poverty rates, and the like. Including these potential mediators as covariates might bias our estimates.⁶ Indeed, one such measure (employment) is an outcome that we evaluate in our analyses.

All models use the NSCH or YRBSS survey weights and cluster SEs at the state level, and we use the “lfe” package (v. 2.8) in R to estimate models by OLS, except as noted.

Table A3. 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 in high school
	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.

Section A6. 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%,⁷ 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 provided in **Figures A2–A3** and **Tables A4–A5**. 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 outcomes. For all other analyses in the appendix, we provide both the uncorrected and corrected CIs.

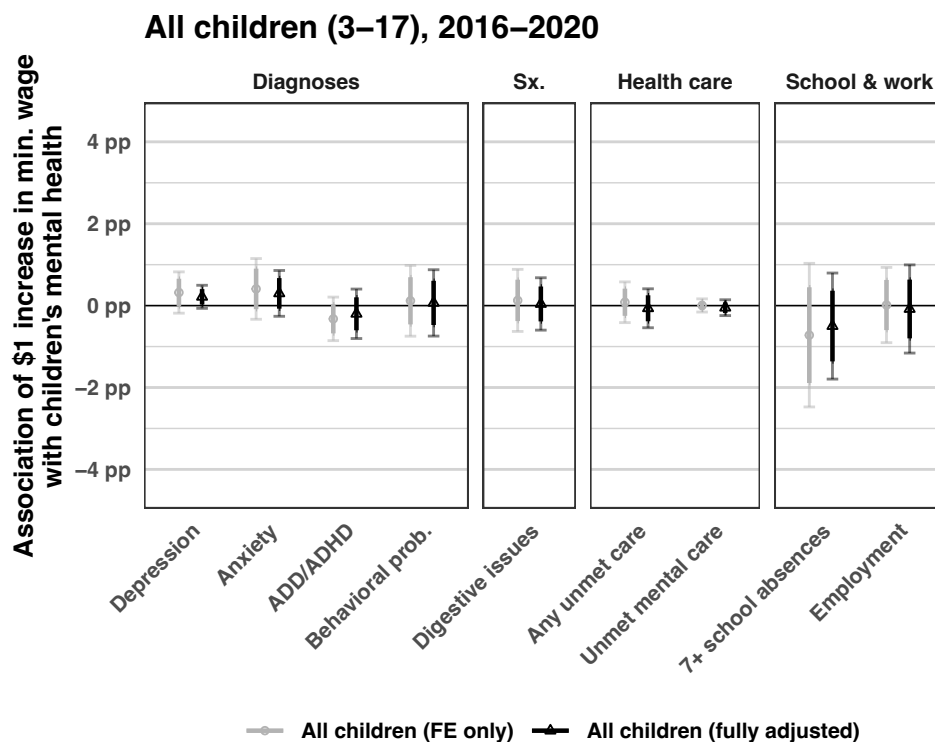


Figure A2. Main TWFE models with Bonferroni corrections for the NSCH.

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 A3**. SEs are clustered at the state level. Exact values in **Table A4**.

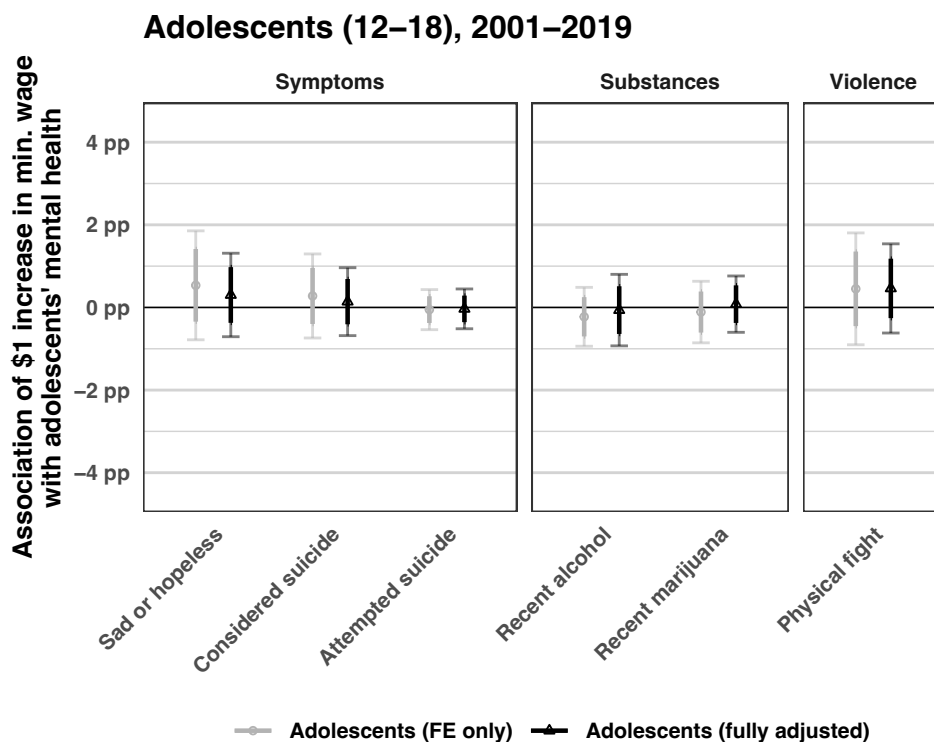


Figure A3. Main TWFE models with Bonferroni corrections for the YRBSS.

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 A3**. SEs are clustered at the state level. Exact values in **Table A5**.

Table A4. Values for the main TWFE models for the NSCH.

	Depression		Anxiety		ADD/ADHD	
	FE only	Fully adj.	FE only	Fully adj.	FE only	Fully adj.
\$1 increase in min. wage	0.3	0.2	0.4	0.3	-0.3	-0.2
95% CIs	[0.0, 0.7]	[0.0, 0.4]	[-0.1, 0.9]	[-0.1, 0.7]	[-0.7, 0.0]	[-0.6, 0.2]
99.7% CIs	[-0.2, 0.8]	[-0.1, 0.5]	[-0.4, 1.2]	[-0.3, 0.9]	[-0.9, 0.2]	[-0.8, 0.4]
Demographic controls	No	Yes	No	Yes	No	Yes
State policy controls	No	Yes	No	Yes	No	Yes
State and year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cluster-robust SEs	State	State	State	State	State	State
Number of adolescents	141,049	141,049	140,998	140,998	140,529	140,529
Adjusted R2	0.002	0.034	0.004	0.038	0.005	0.049

	Behavioral prob.		Digestive issues		Any unmet care	
	FE only	Fully adj.	FE only	Fully adj.	FE only	Fully adj.
\$1 increase in min. wage	0.1	0.1	0.1	0.0	0.1	-0.1
95% CIs	[-0.5, 0.7]	[-0.5, 0.6]	[-0.4, 0.6]	[-0.4, 0.5]	[-0.3, 0.4]	[-0.4, 0.3]
99.7% CIs	[-0.8, 1.0]	[-0.8, 0.9]	[-0.7, 0.9]	[-0.6, 0.7]	[-0.4, 0.6]	[-0.6, 0.4]
Demographic controls	No	Yes	No	Yes	No	Yes
State policy controls	No	Yes	No	Yes	No	Yes
State and year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cluster-robust SEs	State	State	State	State	State	State
Number of adolescents	141,045	141,045	140,518	140,518	141,094	141,094
Adjusted R2	0.002	0.035	0.001	0.005	0.003	0.014

	Unmet mental care		7+ school absences		Employment	
	FE only	Fully adj.	FE only	Fully adj.	FE only	Fully adj.
\$1 increase in min. wage	0.0	-0.1	-0.7	-0.5	0.0	-0.1
95% CIs	[-0.1, 0.1]	[-0.2, 0.1]	[-1.9, 0.5]	[-1.4, 0.4]	[-0.6, 0.6]	[-0.8, 0.7]
99.7% CIs	[-0.2, 0.2]	[-0.3, 0.2]	[-2.6, 1.1]	[-1.9, 0.9]	[-0.9, 1.0]	[-1.2, 1.0]
Demographic controls	No	Yes	No	Yes	No	Yes
State policy controls	No	Yes	No	Yes	No	Yes
State and year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cluster-robust SEs	State	State	State	State	State	State
Number of adolescents	141,094	141,094	114,928	114,928	114,163	114,163
Adjusted R2	0.001	0.005	0.002	0.017	0.017	0.266

Notes: This table details the coefficients, CIs, and Ns for the TWFE models presented in **Figure A2**. Models include the indicated fixed effects, adjustments (per **Table A3**), and clustered SEs.

Table A5. Values for the main TWFE models for the YRBSS.

	Sad or hopeless		Considered suicide		Attempted suicide	
	FE only	Fully adj.	FE only	Fully adj.	FE only	Fully adj.
\$1 increase in min. wage	0.5	0.3	0.3	0.1	-0.1	0.0
95% CIs	[-0.4, 1.4]	[-0.4, 1.0]	[-0.4, 1.0]	[-0.4, 0.7]	[-0.4, 0.3]	[-0.4, 0.3]
99.7% CIs	[-0.9, 1.9]	[-0.8, 1.4]	[-0.8, 1.4]	[-0.7, 1.0]	[-0.6, 0.5]	[-0.5, 0.5]
Demographic controls	No	Yes	No	Yes	No	Yes
State policy controls	No	Yes	No	Yes	No	Yes
State and age-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cluster-robust SEs	State	State	State	State	State	State
Number of adolescents	1,218,309	1,218,309	1,129,583	1,129,583	922,636	922,636
Adjusted R2	0.009	0.043	0.006	0.021	0.005	0.014

	Recent alcohol		Recent marijuana		Physical fight	
	FE only	Fully adj.	FE only	Fully adj.	FE only	Fully adj.
\$1 increase in min. wage	-0.2	-0.1	-0.1	0.1	0.5	0.5
95% CIs	[-0.7, 0.3]	[-0.7, 0.5]	[-0.6, 0.4]	[-0.4, 0.5]	[-0.5, 1.4]	[-0.3, 1.2]
99.7% CIs	[-1.0, 0.5]	[-1.0, 0.9]	[-0.9, 0.7]	[-0.6, 0.8]	[-1.0, 1.9]	[-0.7, 1.6]
Demographic controls	No	Yes	No	Yes	No	Yes
State policy controls	No	Yes	No	Yes	No	Yes
State and age-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cluster-robust SEs	State	State	State	State	State	State
Number of adolescents	1,149,833	1,149,833	1,206,459	1,206,459	965,173	965,173
Adjusted R2	0.051	0.063	0.018	0.022	0.017	0.056

Notes: This table details the coefficients, CIs, and Ns for the TWFE models presented in **Figure A3**. Models include the indicated fixed effects, adjustments (per **Table A3**), and clustered SEs.

Section A7. TWFE Sub-Population Analyses

We tested the association between the minimum wage and the mental health of several 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). These sub-populations are listed in **Table A3**. We performed these analyses by subsetting the dataset to the indicated respondents and re-fitting the main models. This approach is identical to fully interacted TWFE models:

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

whereby the minimum wage variable, all covariates, and all FEs are also interacted with a binary variable, $group_{ist}$, defined for each sub-population such that inclusion = 0 and non-inclusion = 1. For example, Black and Hispanic/Latino children are coded as 0 and all other children who have complete information on race/ethnicity are coded as 1. In the fully interact model, β_3 provides the association for the sub-population of interest, i.e. Black and Hispanic/Latino children.

We provide these subgroup analyses in **Figures A4** and **A5**. There is little evidence of meaningful improvements for any outcome or any sub-population. 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 less educated households in the NSCH but no other sub-populations; (2) do not show a consistent direction within sub-populations, e.g. for less educated households, raising the minimum wage is negatively associated with rates of ADD/ADHD yet no improvements in any other outcomes; (3) do not use an unbiased causal design; and (4) are no longer significant under the 99.7% CIs. As a result, our interpretation of these analyses is that they are generally null.

Table A6. List of sub-population analyses for TWFE models.

Survey	Sub-population
NSCH	Less than 200 FPL%
NSCH	Adults with high school or less <i>That is, all households for which no adult completed more than high school</i>
NSCH	Black or Hispanic/Latino
NSCH	First- or second-generation
NSCH	Adolescents, age 13–17
YRBSS*	Black or Hispanic/Latino

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.

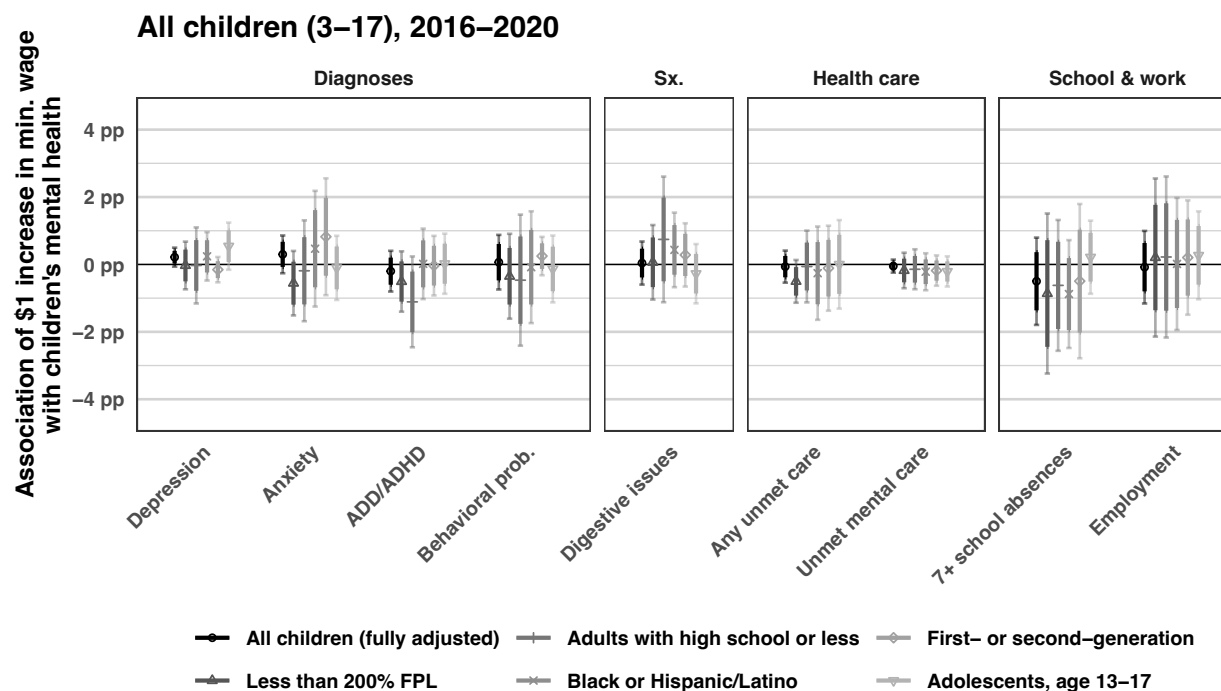


Figure A4. TWFE models for sub-populations in the NSCH.

Notes: Based on OLS TWFE models that re-estimate the main models on a subset of the indicated sub-populations. All models are adjusted for state and year fixed effects, as well as individual- and state-level covariates per **Table A3**. 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.

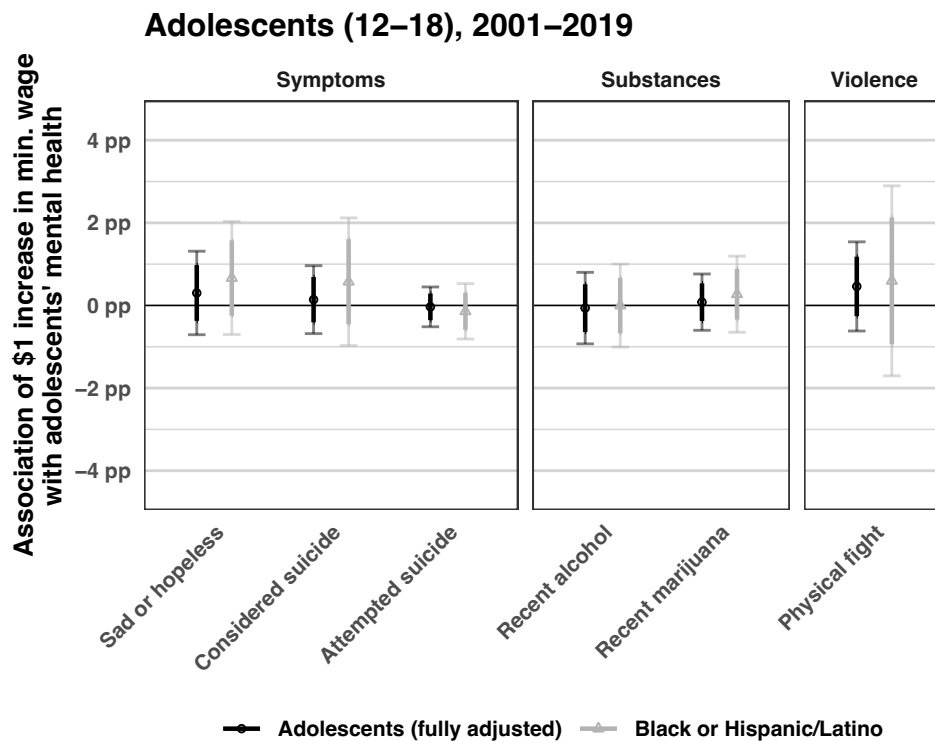


Figure A5. TWFE models for a sub-population in the YRBSS.

Notes: Based on OLS TWFE models that re-estimate the main models on a subset of 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 A3**. 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.

Section A8. 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.⁴ 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 precise 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 within each state's 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.⁸ Such is the case here since we observe all states (plus D.C.). As such, the state-clustered errors may, in principle, overstate the uncertainty in the association between the minimum wage and children's mental health. Meanwhile, the nested errors inflate the number of clusters relative to the true 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**).

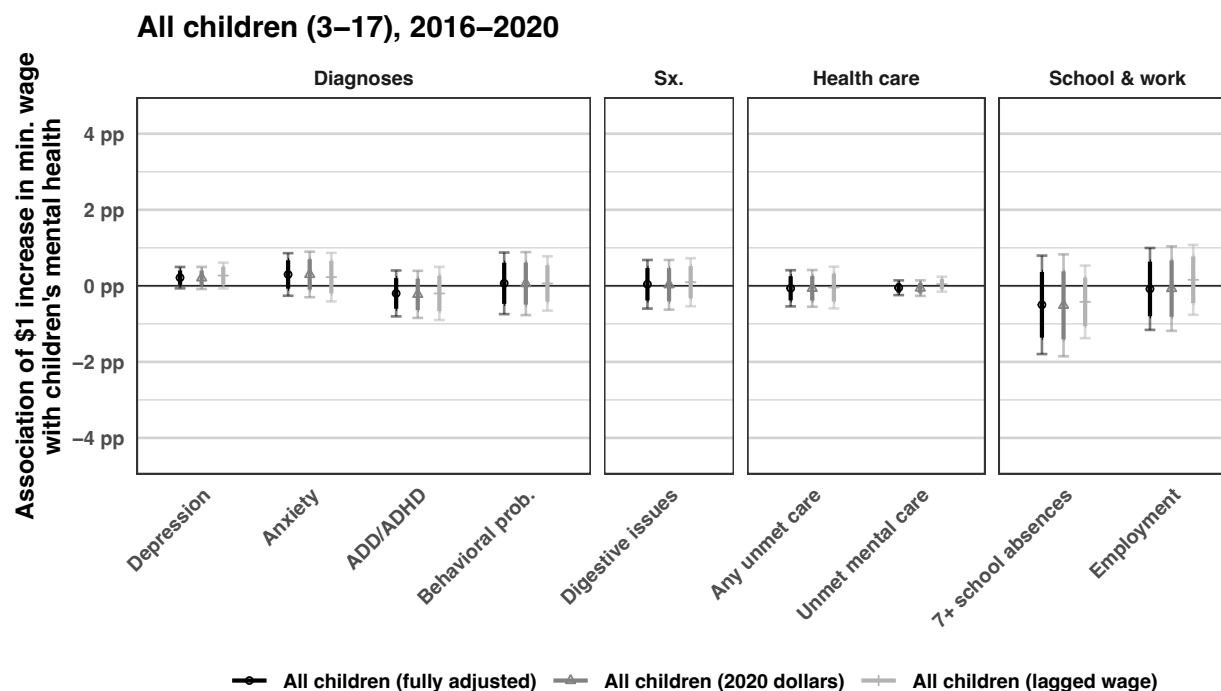


Figure A6. TWFE models with alternative specifications for the NSCH.

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 A3**, 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.

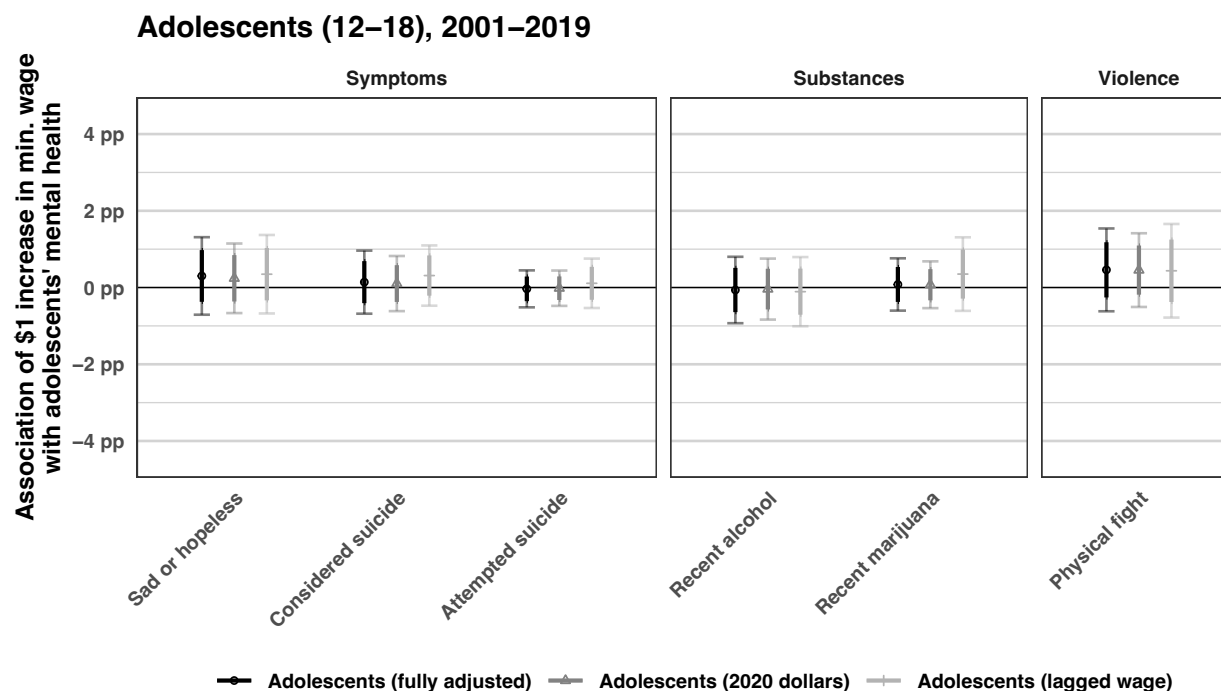


Figure A7. TWFE models with alternative specifications for the YRBSS.

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 A3**, 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.

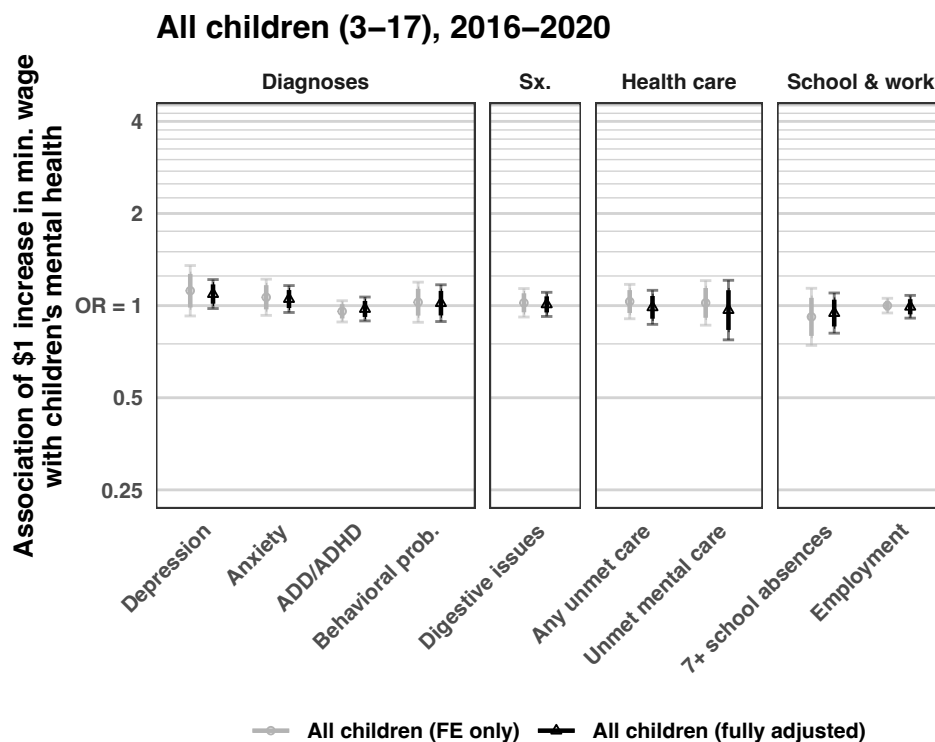


Figure A8. TWFE models using logistic regression for the NSCH.

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 A3**. 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.

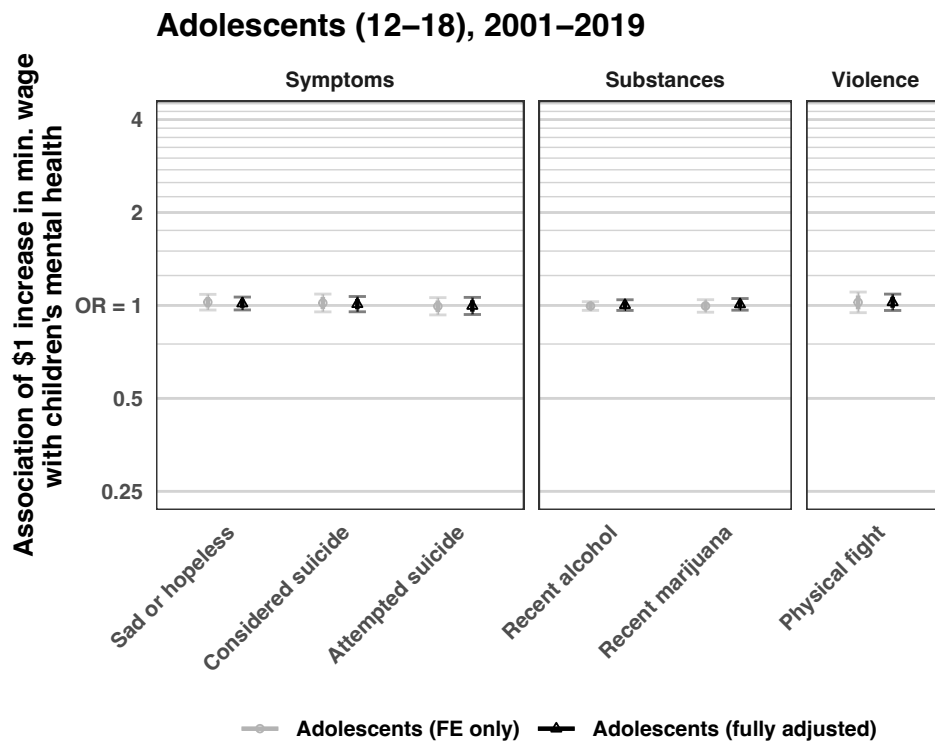


Figure A9. TWFE models using logistic regression for the YRBSS.

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 A3**. 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.

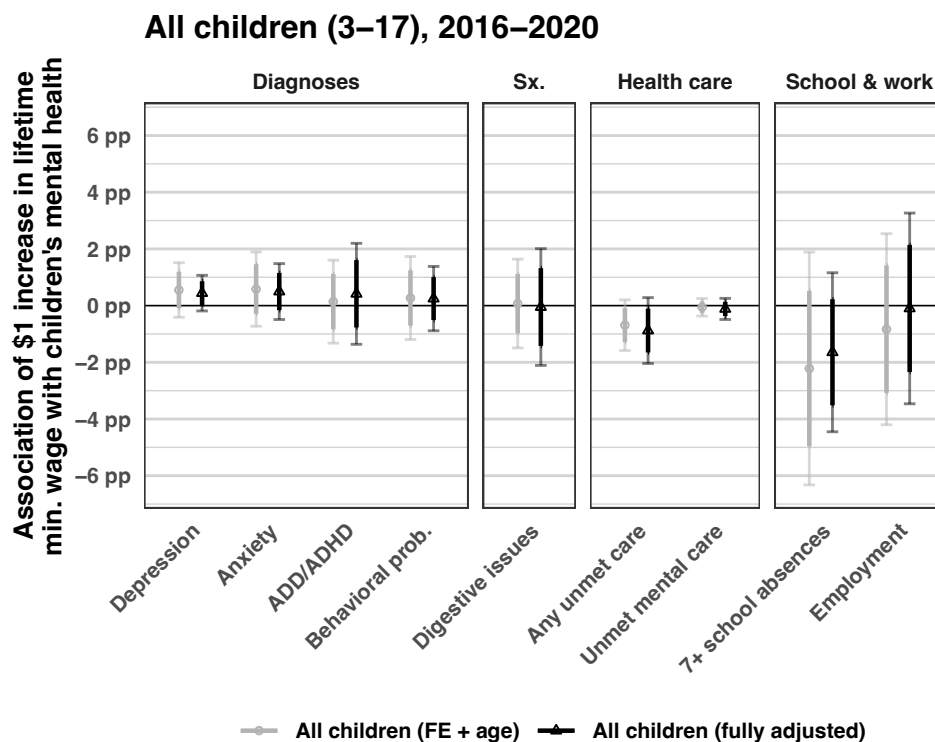


Figure A10. TWFE models using lifetime minimum wages for the NSCH.

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 A3**. 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.

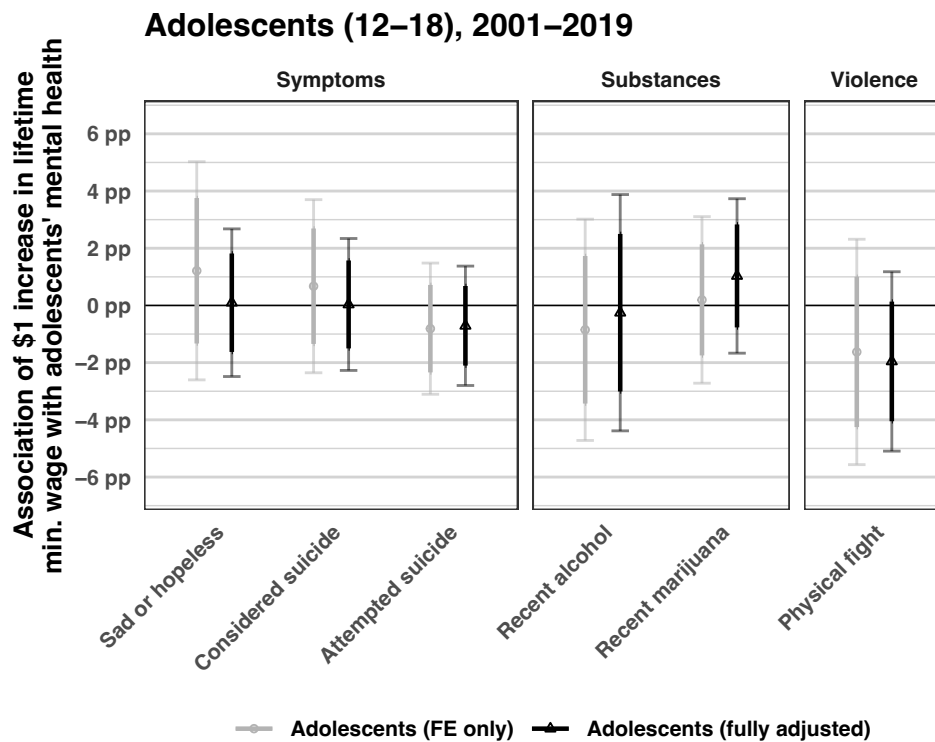


Figure A11. TWFE models using lifetime minimum wages for the YRBSS.

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 A3**. 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.

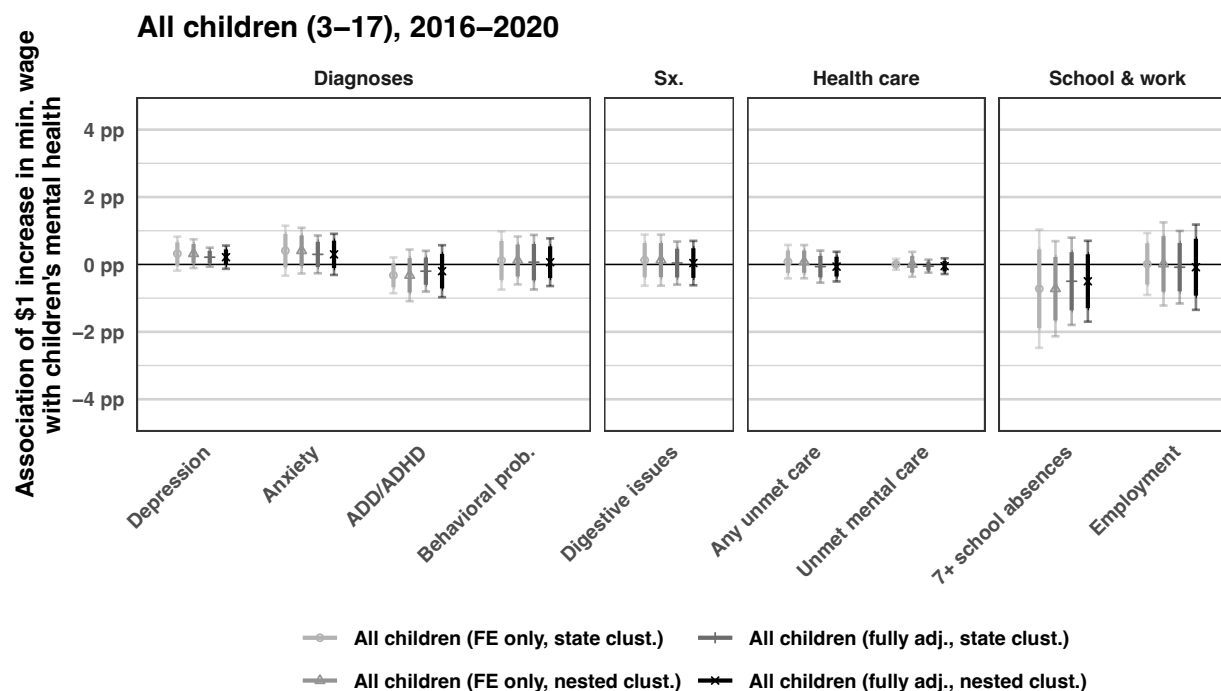


Figure A12. TWFE models using nested clusters for the NSCH.

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 A3**. 95% CIs (thick) and 99.7% CIs for Bonferroni corrections (thin) are provided. N = 114,163 to 141,094.

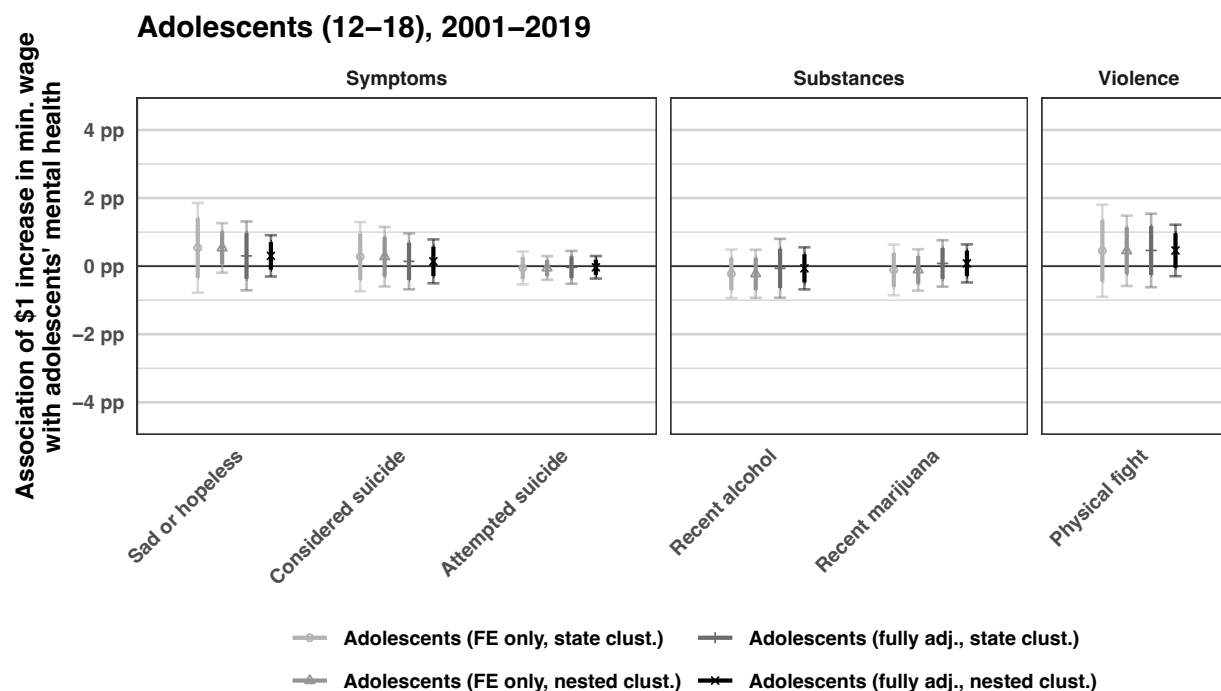


Figure A13. TWFE models using nested clusters for the YRBSS.

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 A3**. 95% CIs (thick) and 99.7% CIs for Bonferroni corrections (thin) are provided. N = 922,636 to 1,218,309.

Section A9. 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.^{9–11} 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 in 2014 or 2015, i.e. 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 of \$7.25 from 2011 to 2019 served as controls. 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:

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

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 A3**); 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:

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

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 A7**, 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**).

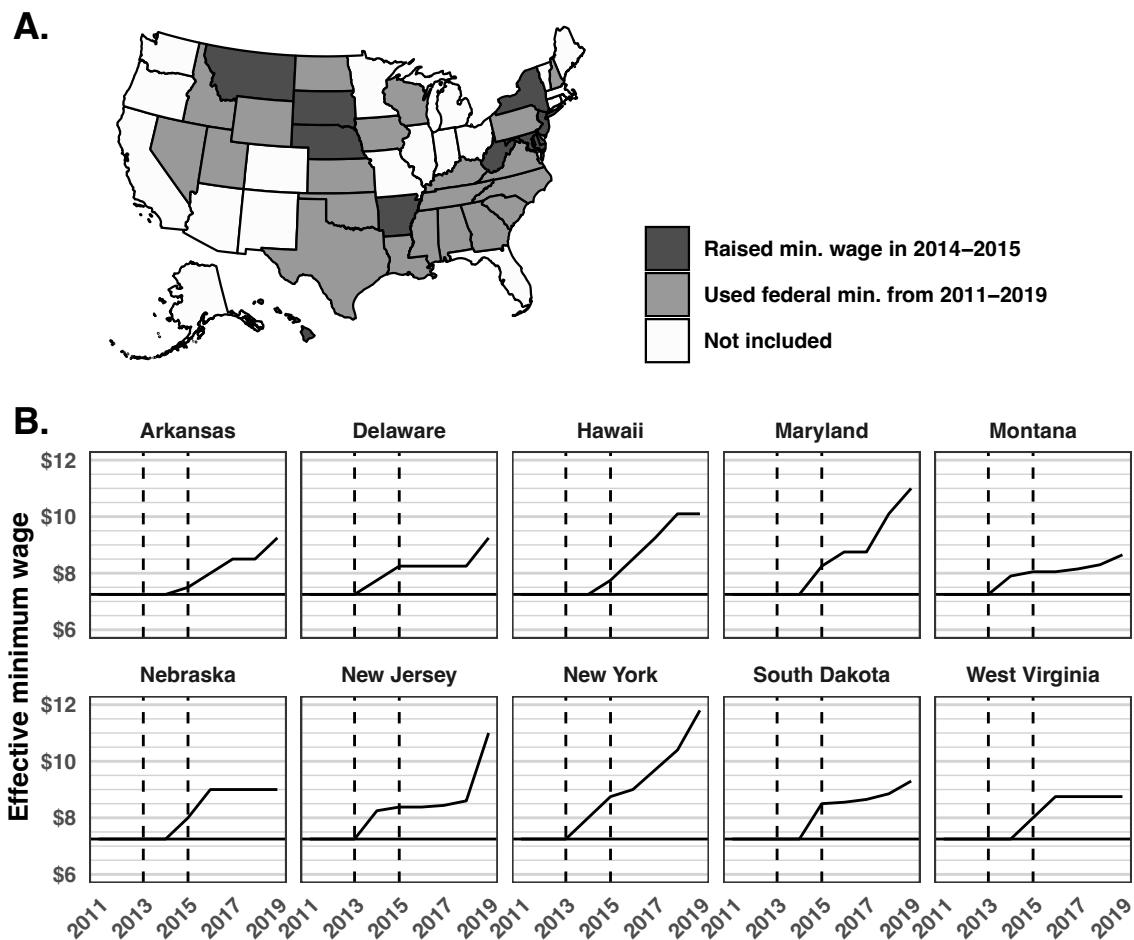


Figure A14. Treatment and control states for difference-in-differences models.

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.

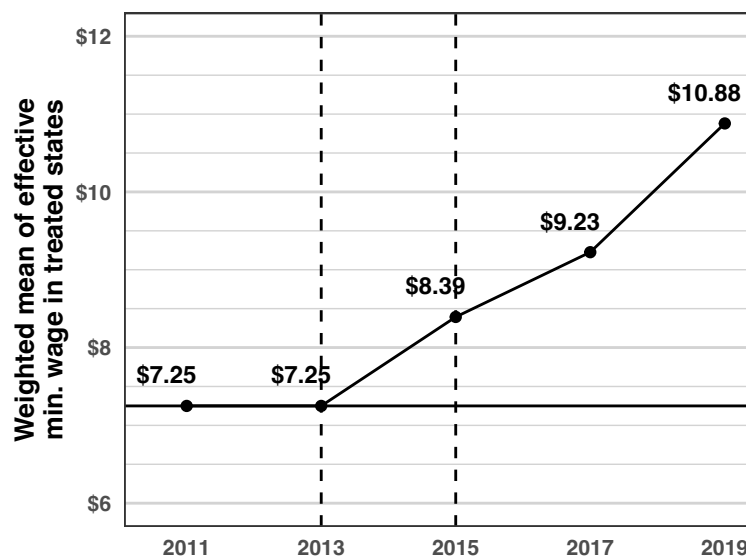


Figure A15. Weighted mean of minimum wage in treatment states.

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 A7. 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 A3**. 95% CIs and 99.2% CIs for Bonferroni corrections are provided.

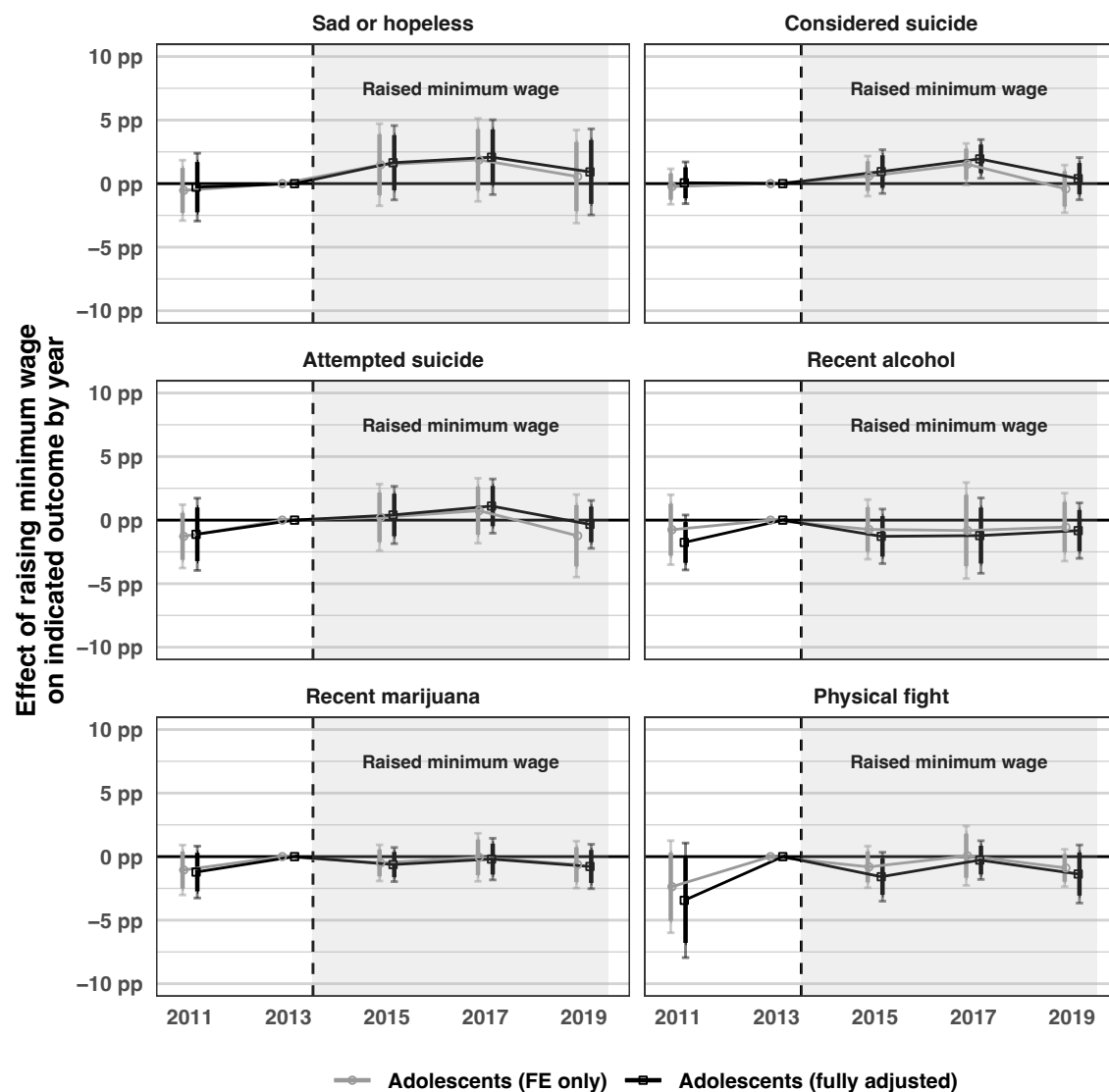


Figure A16. Main event studies using the YRBSS from 2011–2019.

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 A3**. 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.

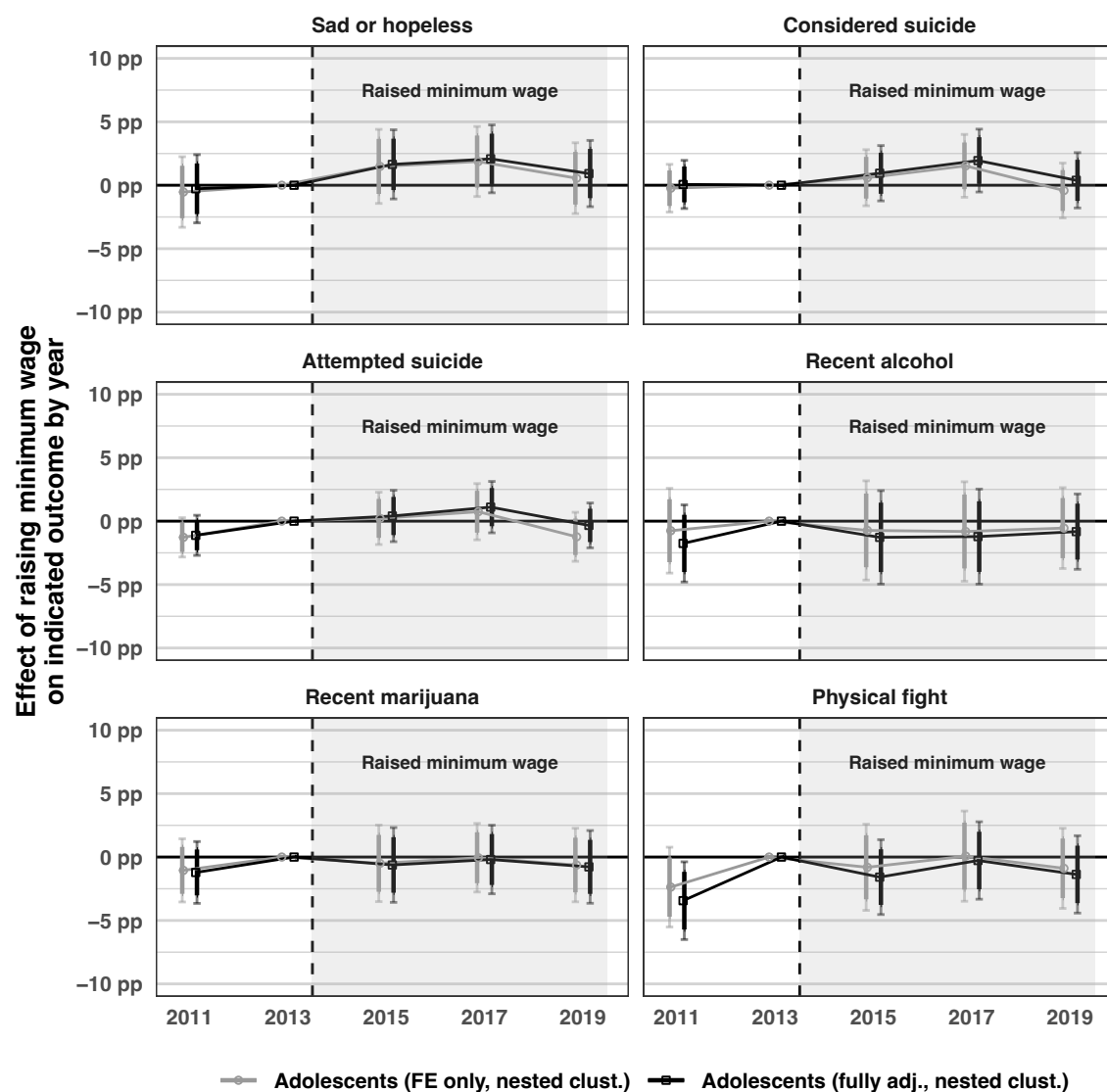


Figure A17. Event studies using nested clusters for the YRBSS.

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 A3**. 95% CIs (thick) and 99.2% CIs for Bonferroni corrections (thin) are provided. N = 311,828 to 553,694.

Section A10. 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.

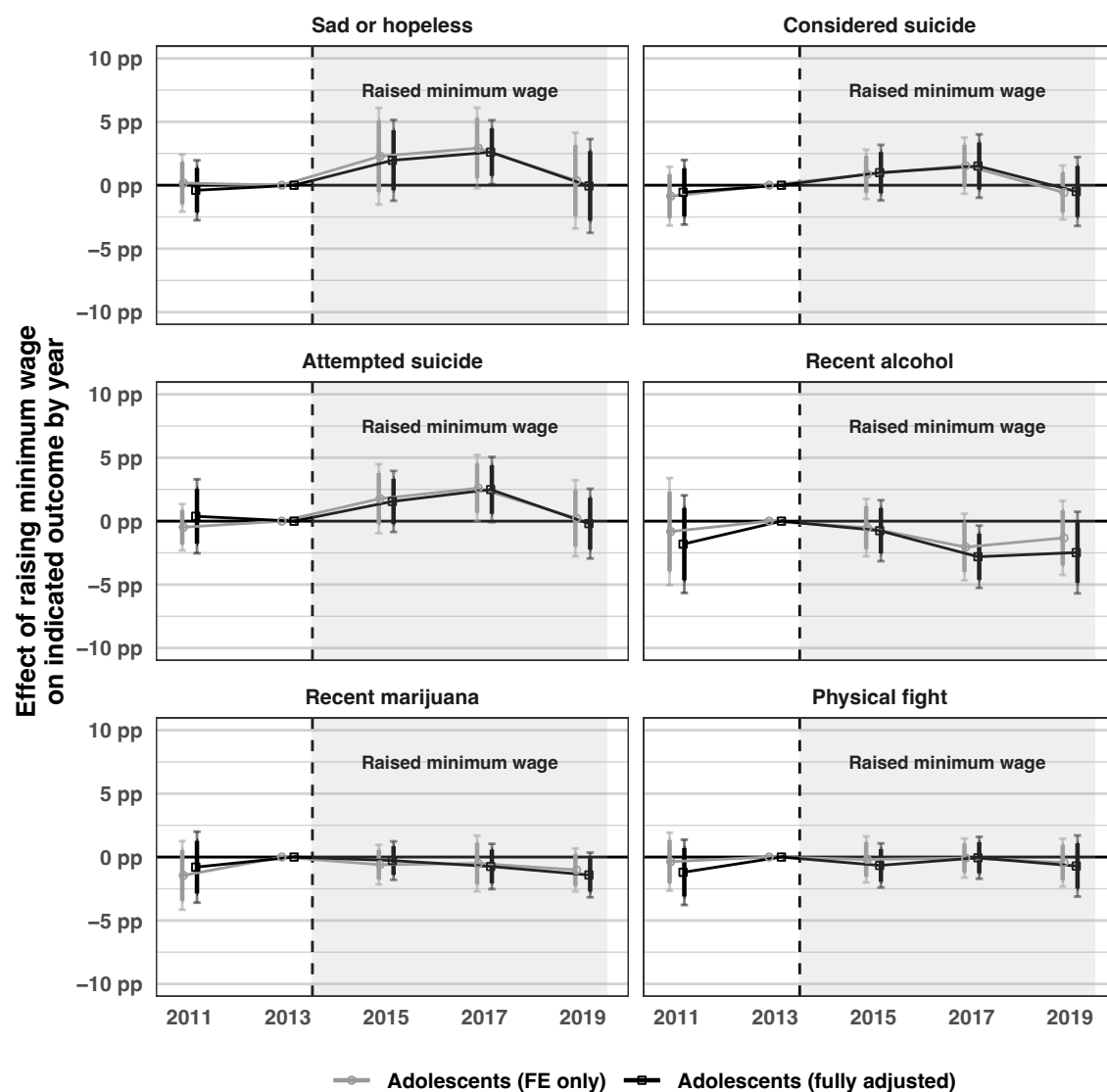


Figure A18. Event studies using a strictly balanced panel for the YRBSS.

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 A3**. 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.

Section A11. References

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