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Anti-Bullying Laws and Youth Risky Health Behaviors*

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Abstract

The U.S. Department of Health and Human Services has urged a coordinated "public health approach" to combatting bullying in schools, in part due to concerns that bullying victimization causes teens to turn to risky health behaviors as a coping mechanism. This study provides new evidence on the effect of anti-bullying laws (ABLs) on youth risky health behaviors. Using data from the Youth Risk Behavior Survey and the National Survey on Drug Use and Health, and a generalized difference-in-differences approach, we find little evidence that ABL adoption leads to statistically significant or economically meaningful reductions in binge drinking, tobacco use, marijuana use, risky sex, or body weight for the average teenager. However, for some historically marginalized youth — particularly those who identify as gay, lesbian, bisexual or questioning (LGBQ) — we find some evidence of ABL-induced improvements in behavioral health, especially with respect to heavier drinking.

Keywords: anti-bullying laws; risky health behaviors; public health

JEL codes: I12; I18; I28

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1. Introduction

> "'[P]robable evidence' of a causal relationship exist[s] between exposure to bullying victimization and illicit drug and tobacco use based on the epidemiological evidence. Possible causal associations existed between bullying victimization and… alcohol use, loneliness, obesity, overweight and psychosomatic symptoms…. More studies are needed to support these tentative associations."
>
> - Moore et al. (2017, p.72)

Bullying is defined as "unwanted, aggressive behavior" among school-age children that involves a power imbalance and has the potential to be repeated (U.S. Department of Health and Human Services 2019). It can take many forms, including name-calling, spreading rumors or lies, physical intimidation, theft, and electronic harassment (Bradshaw et al. 2007; U.S. Department of Health and Human Services 2019). In 2019, 22 percent of students reported being victimized by bullying on school property in the prior year and 16 percent reported being the targets of online bullying (National Center for Education Statistics 2021).

To effectively combat bullying, federal policymakers and public health experts have recommended that its perpetration be treated as a public health concern (National Academies of Sciences, Engineering, and Medicine 2016; Hertz et al. 2013) requiring collaborative efforts by school districts, parents, medical professionals, and the public health community in order to prevent harm to students and rehabilitate offenders (U.S. Department of Health and Human Services 2019).[1] A high profile report from the National Academies of Sciences, Engineering, and Medicine (NASEM) concluded that the "coordinated time and attention" of health care providers is needed to combat this "major public health problem" (MAESM 2016).

Treating bullying as a comprehensive public health problem reflects a wide body of scholarship in public health suggesting a causal link between bullying victimization and a wide set of risky health behaviors, including binge drinking (Topper et al. 2011; Radliff et al. 2012; Priesman et al. 2017; Hertz et al. 2015), tobacco cigarette use (Radliff et al. 2012; Case et al. 2016; Hertz et al. 2015), illicit drug consumption (Priesman et al. 2017; Hertz et al. 2015), risky sexual activity (Hertz et al. 2015; Holt et al. 2013; Litwiller and Brausch 2013), unhealthy dietary and exercise behaviors

[1] The U.S. Department of Health and Human Services has noted that,

> "…professionals from medicine, nursing and public health issued a Call-to-Action in 2000 that instructs communities to adopt a coordinated public health approach to preventing bullying." (Department of Health and Human Services 2019, p. 70)

(Roman and Taylor 2013; Puhl and King 2013; Demissie et al. 2014; Neumark-Sztainer et al. 2002), and self-harm (Fisher et al. 2012; Hay and Meldrum 2010; Karanikola et al. 2018; McMahon et al. 2012). The authors of these studies argue that the likely mechanism to explain these causal links is the adverse mental health effects of bullying (Nikolaou 2017; Rees et al. 2022; Liang et al. 2023), which causes teens to engage in risky health behaviors as a means of coping with or masking psychological harm (Moore et al. 2007).

While a causal link between bullying victimization and risky health behaviors is possible, the empirical approach taken in the public health literature does not rule out other reasons why these outcomes may be correlated. In the main, the public health literature has treated bullying victimization as exogenous to other unmeasured determinants of behavioral health. This assumption may be problematic for a number of a reasons. While those who are bullied clearly do not choose to be victims, they may be non-randomly targeted by perpetrators. For example, perpetrators may bully those who are more vulnerable, who have fewer social support networks, or who have higher personal discount rates (Rees et al. 2022), all of which are characteristics that are difficult-to-observe and also related to risky health behaviors. Bullies may also explicitly target victims who engage in risky behaviors as an observable signal of vulnerability. The research design most often employed in the epidemiological literature — cross-sectional comparisons of risky behaviors between bullied and non-bullied individuals, controlling for baseline demographic characteristics (Moore et al. 2007) — complicates disentangling the causal effect of bullying from an association due to non-random targeting.

This study circumvents one of the empirical challenges faced by prior researchers by exploring the impacts of state anti-bulling laws (ABLs) on youth risky health behaviors. State ABLs require local school districts to implement anti-bullying policies that (i) identify perpetrators and victims of bullying, (ii) punish, educate, and rehabilitate offenders, and (iii) stigmatize bullying behavior. By increasing the probability of detection, increasing punishment, and reducing the psychic benefits of perpetrating bullying, ABLs are hypothesized to raise the expected costs of bullying to potential perpetrators, thus curbing its prevalence.

Reducing youth bullying victimization — and subsequent psychological problems (Rees et al. 2022; Liang et al. 2023; Newman et al. 2005; Hamilton et al. 2008) — is only one channel through which ABLs may reduce teen substance use, risky sex, and unhealthy diet and exercise habits

(Topper et al. 2011; Kuntsche et al. 2007; McFarlane et al. 2005; Neff 1997).[2] ABLs may also reduce youth risky health behaviors through enhanced monitoring of teenagers' behaviors by school faculty and staff (Rees et al. 2022). Moreover, ABLs may also encourage greater parent-child communication about schooling experiences and risky behaviors, which could impact teens' health choices.

On the other hand, ABLs may have unintended consequences that reduce their effectiveness at curbing risky health behaviors among youth. ABLs may shift bullying behavior to off-school premises, where school policies are less binding (Sabia and Bass 2017), or even to electronic bullying. The shifting of bullying to less monitored locations could increase the severity of bullying victimization, resulting in an increase in risky behaviors as a coping mechanism. Moreover, even if ABLs are effective at reducing net bullying victimization, ABLs may prevent youths from developing "thicker skins" in coping with bullying, leaving them more vulnerable to negative emotional shocks in other environments (Hillard et al. 2014). Finally, while bullying is a poor, and perhaps dangerous, method of peer pressure, to the extent that bullying exerts social pressure to encourage healthier behaviors (i.e., healthier diet and exercise habits to avoid being targeted for being overweight), there may be some unintended health costs of preventing negative peer interactions.

Using data from the Youth Risk Behavior Surveillance Surveys (YRBSS) and a two-way fixed effects (TWFE) approach, we find that the adoption of an ABL is associated with a 1.8-to-2.4 percentage point (9-to-12 percent) decline in the probability that a youth reports being the victim of bullying on school property. However, for most teens, we find little evidence that ABLs are associated with statistically significant or economically important declines in binge drinking, tobacco cigarette use, marijuana use, risky sexual behavior, or the likelihood of being overweight or obese. Estimated effects are small in magnitude, often positive, and fairly-precisely estimated. Event-study analyses — including those generated with Callaway and Sant'Anna (2021) estimates that restrict counterfactuals to not-yet-adopters of ABLs — provide support for the parallel trends assumption but produce little evidence that risky health behaviors decline following enactment of an ABL for the average high school student.

[2] A reduction in bullying victimization may also enhance social connectedness (Nansel et al. 2001; Nansel et al. 2004), which could also generate mental health benefits. Moreover, if reductions in bullying victimization increase academic achievement (Eriksen et al. 2014), risky behaviors may decline due to enhanced health knowledge or by raising the opportunity costs of risky behaviors (Li et al. 2015).

However, this does not mean that no students see improvements in risky health behaviors following ABL adoption. For instance, when we turn to vulnerable youth — in particular, teenagers who identify as gay, lesbian, bisexual or questioning (LGBQ) — we find ABL adoption is associated with a statistically significant and economically meaningful reduction in binge drinking. This finding is consistent with recent evidence that LGBQ teens experience relatively large mental health gains from ABL adoption (Liang et al. 2023; Rees et al. 2022), which could suggest a reduced need to turn to alcohol misuse as a means to cope with adverse mental health effects of bullying victimization.

2. Background

2.1 Youth Risky Behaviors

Youths may rationally choose to engage in risky health behaviors if the value of the utility gains from such behaviors exceed the net present discounted value of future costs of these activities (Parsons et al. 1997; Reyna and Farley 2006; O'Donoghue and Rabin 2001). While the utility gains from engaging in risky behaviors are often attributable to a "high" (Gruber and Köszegi 2001) or pleasurable feeling (Moschion and Powdthavee 2018), including greater social status among peers (Prince et al. 2015; Kuntsche et al. 2007), utility gains may also serve as an immediate "escape" or means of coping with stress (Pelham at al. 1997; Colder et al. 2002; Topper et al. 2011), depression (Topper et al. 2011), or relationship problems (Liebschutz et al. 2002; Grotpeter and Crick 1996; Carlyle and Steinman 2007).

Government intervention to reduce risky behaviors among teenagers is often justified on efficiency grounds due to (i) imperfect information on the benefits and costs of such activities (Cawley and Ruhm 2011), (ii) hyperbolic discounting of future consequences (O'Donoghue and Rabin 2001), and (iii) negative externalities for such behaviors (Cawley and Ruhm 2011). A wide set of studies in the health economics literature has studied the responsiveness of teen risky health behaviors to public policies that affect access,[3] as well as the role of peers in influencing risky behaviors[4], with each literature concluding important roles.

[3] A wide literature in health economics has explored teenagers' responsiveness to public policies that affect the price of tobacco use (Anderson et al. 2020; Hansen et al. 2017; Carpenter and Cook 2008), alcohol consumption (Carpenter and Dobkin 2009; Carpenter 2004; Carpenter et al. 2007; Dent et al. 2005), illicit drug use (Anderson et al. 2019; Wen et al. 2015; Kenkel et al. 2001; Pacula et al. 2015), risky sexual behavior (Bass 2019; Rees and Sabia 2013; Sabia 2006), and unhealthy dietary and exercise habits (Cawley and Maclean 2013, 2007; Sabia et al. 2017; Millimet et al. 2010; Bhattacharya et al. 2006; Gleason and Suitor 2003; Campbell et al. 2011).

[4] The empirical approaches used in this literature have sought to disentangle peer effects from common environmental shocks and endogenous reflection (Manski 1993). Studies using a school fixed effects approach to address common

The relationship between psychological health and risky behaviors among teenagers and young adults has increasingly been studied by both health economists and public health researchers (Pesko 2012, 2014; Fletcher and Sindelar 2012; Pendersen 2013; Kurspahić-Mujčić et al. 2014; Gustavsen et al. 2016; Latif 2014). There is evidence that negative psychological shocks generated from natural disasters (Pesko 2012), war-related events (Pesko 2014; Cesur and Sabia 2016), and family stress (Fletcher and Sindelar 2012; Gustavsen 2013) are linked to risky health behaviors among youths. Recent evidence also suggests that exogenous negative emotional shocks from college sporting events may induce alcohol-related violence among youths (Rees and Schnepel 2009; Merlo et al. 2010; Lindo et al. 2018).

2.2 Bullying and Youth Risky Health Behaviors

The conclusion reached by the National Academies of Sciences, Engineering, and Medicine (2016) that "bullying behavior is a major public health problem" is based, in part, on a wide set of epidemiological studies that have found strong evidence of a positive association between bullying victimization and risky health behaviors.[5] A series of studies using a single cross section of the National Youth Risk Behavior Survey have found that bullying victimization is positively related to substance use, including alcohol consumption (Priesman et al. 2017; Hertz et al. 2015), smoking (Case et al. 2016; Hertz et al. 2015), and marijuana use (Priesman et al. 2017; Hertz et al. 2015).[6] Overall, these studies attribute the increase in substance use among teens as a coping mechanism in response to increased stress from bullying victimization.[7]

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shocks have found evidence of peer effects in binge drinking (Lundborg 2006; Gaviria and Raphael 2006; Fletcher 2012), illicit drug use (Lundborg 2006; Gaviria and Raphael 2006; Kawaguchi 2004), risky sexual activity (Card and Giuliano 2013; Bongardt et al. 2015) and obesity (Trogdon et al. 2008; Halliday and Kwak 2009). Other studies have exploited natural experiments to address endogenous peer selection. Using conditional random assignment of college roommates to identify the effects of exogenous exposure to peers, several studies have found evidence of peer effects in binge drinking (Eisenberg et al. 2014; Duncan et al. 2005; Guo et al. 2015), obesity (Yakusheva 2011; Carrell et al. 2011), and marijuana use (Li and Guo 2020). Similar findings have emerged when examining the risky behavior effects of exposure to older school peers using kindergarten start dates as a source of exogenous variation in peer age (Argys and Rees 2008). Together, the findings in these papers support the notion of contagious peer effects in risky behaviors, particularly in the context of the schooling environment.

[5] There is also evidence that bullying victimization impacts many risk factors for risky health behaviors, including stress (Pesko 2012; Kurspahić-Mujčić et al. 2014; Pedersen 2013), social connectedness (Kadushin 2012), and psychological health (Rees et al. 2020; Hansen and Lang 2014; Beckerman and Auerbach 2014).

[6] In another U.S.-based study, Radliff et al. (2012) use data from 16 U.S. school districts across a large Midwestern metropolitan area and find that victims of bullying are more likely to reporting drinking, smoking, and consuming marijuana. A similar pattern of result has been uncovered in the United Kingdom (Topper et al. 2011).

[7] Historically marginalized youths, who are bullied more frequently than their less marginalized counterparts (Daley et al. 2007; Kosciw et al. 2012; Rees et al. 2020), may be more likely to turn to risky health behaviors in response to

There is also evidence that bullying is associated with an increased likelihood that teens engage in sex without condoms (Hertz et al. 2015; Litwiller and Brausch 2013), have sex with multiple sex partners (Hertz et al. 2015), and engage in sexual activity while under the influence of alcohol or drugs (Holt et al. 2013). These findings are interpreted by the authors as evidence that adolescents seek out sexual pleasure as a means of escaping the negative psychological consequences of bullying victimization.

Finally, there is evidence that bullying victimization is associated with reduced time spent in physical activities (Roman and Taylor 2013; Puhl and King 2013; Demissie et al. 2014), increased risk of eating disorders (Puhl and King 2013; Neumark-Sztainer et al. 2002), and a higher probability of being overweight or obese (Baldwin et al. 2016; Mamun et al. 2013). The authors attribute these results to bullying-induced increases in psychological distress, substance abuse and diminished self-esteem. They also suggest that teens victimized by bullying may be more likely to skip physical education classes to avoid interacting with perpetrators.

While the conclusions of the above studies are intriguing, each treats bullying victimization as econometrically exogenous to risky health behaviors. This assumption may be problematic if bullies target their victims based on difficult-to-measure characteristics that are correlated with risky health behaviors such as personal discount rates or family support. Moreover, bullying and substance use may co-occur in schooling environments with less engaged parents and teachers. These confounders make it difficult to interpret the empirical evidence in the epidemiological literature as causal in nature.

2.3 Anti-Bullying Laws and Psychological Health

To circumvent the non-random selection of bullying victims, an emerging literature has examined the impact of state anti-bullying laws, a plausibly exogenous source of variation in bullying behavior, on school safety and psychological wellbeing. Sabia and Bass (2017) find that anti-bullying laws, particularly those that are more comprehensive, lead to a reduction in bullying victimization, improvements in school safety, and a reduction in the likelihood of a school shooting in a given state-year (Sabia and Bass 2017).

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victimization. For example, there is evidence that bullying victimization among Lesbian, Gay, Bisexual, Transgender (LGBT) youth is associated with a substantial increase in the risk of alcohol abuse (Reisner et al. 2015) and illicit drug use (Reisner et al. 2015; Duncan et al. 2014).

Three recent studies have examined the psychological effects of ABL adoption. Rees et al. (2022) finds that ABL adoption is associated with a reduced likelihood of suicidal behaviors, particularly among females and racial minorities. Specifically, they find that state ABLs are associated with a 10 to 20 percent reduction in completed suicides among females ages 14-through-18. Nikolaou (2017) finds a similar pattern of mental health results when studying anti-cyberbullying laws.[8] Finally, Liang et al. (2023) study the impact of state ABL adoption on suicidal behaviors among lesbian, gay, bisexual, and questioning (LGBQ) teenagers and find that gay and lesbian-identifying students experience the largest reductions in suicidal behaviors following ABL adoption relative to heterosexuals or other sexual minorities. Together, these studies suggest that historically marginalized teens experience the largest mental health benefits from ABLs.

Only one published study of which we are aware has studied the relationship between anti-bullying policies and risky health behaviors. Nikolaou (2022) estimates a structural model in which he identifies the effect of bullying using changes in (heterogeneous types of) anti-cyberbullying laws (ACBLs) and ABLs as instruments. The results suggest that more intensive bullying victimization is associated with an increase in substance use among women and an increase in risky sex among men.

While Nikolaou (2022) makes an important contribution to the bullying-risky behaviors literature — in particular, by moving it beyond cross-sectional epidemiological studies described above, which treat bullying victimization as econometrically exogenous — it is worth noting that ACBLs and ABLs could directly affect the risky health behaviors of high school students, violating the exclusion restriction. For instance, anti-bullying laws could encourage monitoring (both online and in school) by school personnel and parents, which in turn could help identify students at risk for engaging in risky health behaviors. Moreover, it is worth noting that Nikolaou (2022) did not estimate the reduced form estimates of the relationship between anti-bullying laws and risky health behaviors.

3. Data

3.1 Anti-Bullying Laws (ABLs)

[8] Nikolaou (2017) examines the relationship between a particular type of bullying victimization - cyberbullying - and youth suicidal behaviors. Using anti-cyber-bullying laws (ACBLs) as an instrument for cyberbullying, he finds that cyberbullying victimization is associated with a 14.5 percentage point increase in suicidal thoughts and an 8.7 percentage point increase in suicide attempts. However, Rees et al. (2020) offers important critiques of the identification strategy employed in this paper, including the possibility that the exclusion restriction may be violated. This may be because anti-cyberbullying laws directly affect (i) parental and school staff monitoring of youth behaviors, or (ii) the provision of mental health services to teens.

Between 1997 and 2019, all 50 states and the District of Columbia adopted some form of ABL. We define an ABL as a state mandate requiring local school districts implement anti-bullying policies. Such mandates often involve requiring the school district to develop (i) written records of the alleged incident of bullying and its resolution, (ii) documentation of an investigatory procedure for incidents of bullying victimization, (iii) a policy for imposition of sanctions on perpetrators for their bullying behavior, (iv) training programs for teachers, staff, and parents to identify bullying behaviors, and (v) clear definitions of student behaviors that constituted bullying.

Table 1 shows the effective dates by which states mandated that school districts enact anti-bullying policies. Figure 1 shows the geographic and temporal rollout of state ABLs. Louisiana was the first state to require school districts to implement anti-bullying policies (August 1, 2001), followed by Colorado (August 8, 2001), and West Virginia (December 1, 2001). Montana was the very last to mandate that school anti-bullying policies be implemented (April 21, 2015).

To address heterogeneity across state ABLs, we identify the five policy components most likely to increase the cost of bullying. These components require school districts to (i) maintain written records of anonymously reported incidents of bullying and their resolution, (ii) implement investigatory procedures for incidents of bullying, (iii) impose detailed consequences and sanctions for bullying incidents, (iv) develop and provide training resources to teachers, staff, and parents on preventing, identifying, and responding to bullying and maintaining open communication among groups, and (v) clearly define the behaviors and actions that constitute bullying. Using Department of Education ratings for each of these components (U.S. Department of Education 2011; U.S. Department of Health and Human Services 2016; Sabia and Bass 2017; Rees et al. 2020), we rate a policy component as "strong" if the rating score exceeds two on a five-point scale. Following Rees et al. (2020), we then define *Stronger ABL* as an ABL with three or more strong policy components and *Weaker ABL* as an ABL with fewer than three strong policy components.

3.2 Youth Risk Behavior Surveillance Surveys

The primary data source for this analysis uses repeated cross-sectional data drawn from the National and State Youth Risk Behavior Surveillance Surveys (YRBSS). The YRBSS is a biennial school-based survey coordinated by the Centers for Disease Control and Prevention (CDC) and made available by both the CDC and state Departments of Health and Human Services and Education. When weighted appropriately, these data can be made representative of U.S. high school

students attending 9th through 12th grades.[9] These pooled surveys have been increasingly used by health economists to estimate the behavioral impacts of a wide set of health- and school-related public policies.[10]

Our analysis sample consists of 1,497,685 U.S. high school students interviewed during the 1997 through 2019 waves of the YRBS who provide non-missing information on risky health behaviors and observable individual demographic controls. Our analysis of bullying victimization is restricted to the 2009-2019 period when bullying is consistently measured.[11]

To test whether ABLs affect the likelihood that a teen is bullied, we first create a measure of *Bullying Victimization*, a dichotomous variable set equal to 1 if the respondent reported having "been bullied on school property" during the prior year, and 0 otherwise. In our analysis sample (across all treatment and control states, pre- and post-ABL adoption), 19.2 percent of respondents reported being bullied in the last 12 months.

We then turn to our measures of risky health behaviors. *Binge Drinking* is a dichotomous variable set equal to 1 if the respondent reported having had "5 or more drinks of alcohol in a row within a few hours" during the prior 30 days, and 0 otherwise. [12] We find that 22.6 percent of respondents reported binge drinking in the last 30 days.

Second, *Tobacco Cigarette Use* is set equal to 1 if the respondent reported s/he had "smoke[d] cigarettes" on one or more days in the prior 30 days, and 0 otherwise. In our sample, 18.5 percent reported smoking a cigarette in the prior month. *Marijuana Use* is measured analogously, with 21.0 percent of high school students reporting consuming marijuana in the prior month.

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[9] Adjusted population weights are generated from the Surveillance Epidemiology and End Results Program (http://seer.cancer.gov/popdata/). See Anderson et al. (2019) for a discussion.

[10] For example, these datasets have been used to estimate the impacts of cigarette taxes (Anderson et al. 2020; Hansen et al. 2013, 2017), medical marijuana laws (Anderson et al. 2015, 2019), minimum wages (Sabia et al 2019), sex education (Bass 2019), parental involvement laws for abortion (Sabia and Anderson 2016), and anti-bullying laws (Sabia and Bass 2017; Rees et al. 2022).

[11] We also experiment with restricting our risky behavior analysis to the 2009-2019 period to match the "first stage" effects of ABLs.

[12] In 2017, the wording of this questionnaire item changed to, "During the last 30 days, on how many days did you have 4 or more drinks of alcohol in a row (if you are female) or 5 or more drinks in a row (if you are male)?" Thus, there may be a level change in rates of binge drinking for women who drank 4 or more drinks in a row, who would be classified as binge drinkers in 2017, but not in prior waves of the survey. If this level change is common across states, year fixed effects in our difference-in-differences model should capture this measurement change. However, when we limit the sample to the 1997-2015 and 2009-2015 periods, we find a qualitatively similar pattern of results. Moreover, as discussed below, when we show results exclusively for men for whom measurement of binge drinking behavior did not change, the results are qualitatively similar.

Next, we characterize risky sex behavior using a measure of whether the respondent had used contraception during their most recent intercourse. *Risky Sex* is coded equal to 1 if the student reported that the last time they had sexual intercourse, "neither s/he nor her/his partner had used a condom at last intercourse." This variable is set equal to 0 if the respondent had "never had sexual intercourse" or a condom was used at most recent intercourse. We find that 16.8 percent of respondents in our analysis sample reported engaging in recent risky sexual intercourse.

Finally, respondents are asked to report how "tall [you are] without your shoes on" and how much they "weigh without your shoes on." From these measures, we construct the variable *BMI*. This is the respondent's self-reported body mass index, calculated as the ratio of weight (in kilograms) to squared height (in meters). The average reported BMI in our analysis sample is 23.3. Then, we generate an indicator for *Overweight or Obese,* set equal to 1 if the respondent's BMI is at or above the 85th percentile for their age and gender.[13] We find that 28.5 percent of respondents are classified as either overweight or obese using this definition.[14]

Table 2 shows the weighted means of each of the above risky behaviors for 1997-2019, both for the full sample and by whether an ABL was enacted in the state-year. Overall, we find that rates of risky health behaviors were lower in state-years when an anti-bullying law was enacted. For example, we find that 18.4 percent of teenagers engaged in binge drinking behavior in state-years when an anti-bullying law was enacted, compared to 27.2 percent when it was not. However, this pattern could simply reflect (i) differences in propensity for risky behaviors *across* states that enact anti-bullying laws, or (ii) national time trends in risky behaviors, given that all states had enacted ABLs by 2015. To isolate the effect of ABLs from such spurious factors, we use the regression framework outlined in Section 3.3 below.

Figures 2 and 3 show trends in the dependent variables. We find evidence that many of the risky health behaviors under study (binge drinking, tobacco use, and risky sex) declined throughout the 2000s and 2010s. However, the share of U.S. high school students classified as overweight or obese rose from 24.9 percent in 1999 to 31.6 percent in 2019. Youth marijuana use fell from 1997 through 2007, before rising between 2007 and 2011, and declining to 19.2 percent in 2019.

[13] Calculations of the 85th percentile calculations are based on age and sex-specific reference data from the 2000 CDC growth charts.

[14] While body weight is not, itself, a risky health behavior, its incidence is related to risky behaviors related to diet and exercise habits.

3.3 *National Survey on Drug Use and Health (NSDUH)*

To supplement our YRBS-based analysis, we draw data on 12-to-17-year-olds from the publicly available National Survey on Drug Use and Health (NSDUH). The NSDUH is administered by the Substance Abuse and Mental Health Services Administration (SAMSHA). It is a household survey designed to be representative of the U.S. non-institutionalized population. The survey is administered in individuals' homes (including private homes, public housing, and non-institutional group quarters such as college dorms, rooming houses, shelters). To address concerns of privacy and increase the likelihood of a truthful response, the survey is conducted via an individual audio computer-assisted self-administered interview. One advantage of the NSDUH over the YRBS is that the data include information on risky behaviors of teenagers who drop out of high school.[15]

Our analysis sample makes use of publicly available two-year overlapping state-by-year prevalence rates of (i) binge drinking, (ii) marijuana use, and (ii) illicit drug use other than marijuana among 12-to-17-year-olds. Our data span the period 2002-2020. *Binge Drinking* is defined as "drinking five or more drinks (for males) or four or more drinks (for females) on the same occasion (i.e., at the same time or within a couple of hours of each other) on at least one day in the past 30 days." We find that 8.4 percent of 12-to-17-year-olds reported binge drinking.

Turning to drug use, *Marijuana Use* is defined as the number of days in the last month on which the respondent "use[d] marijuana or hashish." We find that 7.4 percent of 12-to-17-year-olds reported consuming marijuana in the last 30 days. In addition, *Illicit Drug Use Other than Marijuana* is defined as "use[d] an illicit drug other than marijuana (Includes heroin, hallucinogens, inhalants, cocaine, and the nonmedical use of prescription-type pain relievers, tranquilizers, stimulants, and sedatives)." We find that 4.3 percent of 12-to-17-year-olds reported consuming illicit drugs other than marijuana in the prior 30 days.

Finally, as a pseudo-falsification exercise, we examine these outcomes (binge drinking, marijuana use, and illicit drug use other than marijuana) for those ages 18-to-25. (The publicly available NSDUH data do not allow us to disaggregate 18-to-25-year-olds further by age.) ABLs are not expected to contemporaneously affect risky health behaviors of most 18-to-25-year-olds, who

[15] We note, however, that there is little evidence that ABL adoption affects the probability of dropping out of high school. Thus, sample selection bias is likely not a first-order concern with the YRBS (see Rees et al. 2022 and Appendix Table 1).

are beyond their high school years when ABLs may affect contemporaneous risky health behaviors. However, if there are lagged effects of ABLs (for instance, effects that impact longer-run risky health behaviors through impacting trajectories of health decision-making), one could still imagine that ABLs could affect young adults' risky health behaviors.[16] Moreover, some 18-year-olds are still in high school and their behavior could be contemporaneously affected by an ABL. Finally, given that some 18-to-25-year-olds no longer reside in the state where they went to high school (i.e., because they attended a college out of state), we may be mismatching ABL policies (in high school) to the individual's current state of residence. For each of these reasons, we do not categorize estimates of the effects of ABLs on risky health behaviors of 18-to-25-year-olds as true placebo tests, and rather view the results on this age group as merely suggestive. We find that 41.8 percent of 18-to-25-year-olds had engaged in prior-month binge drinking, 18.7 percent consumed marijuana in the last 30 days, and 8.0 percent used illicit drugs other than marijuana in the last 30 days.

4. Empirical Approach

We begin by exploring the "first-stage" relationship between state ABLs and bullying victimization by estimating a two-way fixed effects (TWFE) difference-in-differences model of the following form via ordinary least squares (OLS):

$$\text{Bullying Victimization}_{ist} = \beta_0 + \beta_1 ABL_{st} + \mathbf{Z'}_{it}\,\boldsymbol{\beta_2} + \mathbf{X'}_{st}\,\boldsymbol{\beta_3} + \alpha_s + \pi_t + \varepsilon_{ist} \quad (1)$$

where *Bullying Victimization* measures whether high school student *i* residing in state *s* in year *t* reports being bullied on school property in the prior 12 months, ABL_{st} is an indicator for whether an ABL has been enacted in state *s* in year *t*; $\mathbf{Z}_{it}$ is a vector of individual-specific demographic controls including gender, age, grade, and race/ethnicity; and survey (state or national YRBS) fixed effect, $\mathbf{X}_{st}$ is a vector of state-specific time-varying economic controls (unemployment rate, per capita income, and share of population with a bachelor's degree), education policy-related controls (average teacher salary, average pupil/teacher ratio).[17] In addition, we also explore the sensitivity of our estimate of β_1

[16] For instance, a 19-year-old's health behavior measured two years after an ABL was adopted in her state could be affected by an ABL if her behavior at age 17 were contemporaneously affected and this behavioral effect persisted over time.

[17] While we also considered including controls for zero tolerance school violence laws, there was little to no variation in their adoption during the 2009-2019 or 1997-2019 periods.

to the inclusion of controls for public policies that might affect risky health behaviors, including school health policies (sex education mandates and physical education credit requirements), tobacco control policies (per-pack cigarette taxes, per mL nicotine fluid e-cigarette tax), marijuana policies (medical marijuana laws, recreational marijuana laws), and alcohol policies (beer taxes); in addition, α_s is a time-invariant state effect; and π_t is a state-invariant year (wave) effect.

After establishing a "first stage" bullying effect, we next turn to our risky behavior outcomes using a similar regression approach:

$$R_{ist} = \gamma_0 + \gamma_1 ABL_{st} + \mathbf{Z'}_{it}\,\boldsymbol{\gamma_2} + \mathbf{X'}_{st}\boldsymbol{\gamma_3} + \alpha_s + \pi_t + \mu_{ist} \quad (2)$$

where R_{ist} measures the risky behavior (see above) of student *i* in state *s* in year *t*.[18]

Identification of our key parameters of interest, β_1 and γ_1, comes from geographic and temporal variation in ABL adoption. Key threats to generating unbiased estimates of β_1 and γ_1 include (i) state-specific time-varying unobservables that are correlated with both the adoption of ABLs and youth risky health behaviors, and (ii) reverse causality. To test whether our identifying assumptions are valid, we undertake several strategies. First, we explore the stability of the estimates of β_1 and γ_1, to the inclusion of the observable controls in $\mathbf{X}_{st}$. If ABLs are adopted exogenously to this wide set of observables, then the estimates of β_1 and γ_1 should be quantitatively similar across specifications that include limited controls as compared to a more fully saturated model.

Second, we conduct event-study analyses to test whether pre-treatment trends in youth risky health behaviors were similar in treatment and control states. If estimates of the lead effects were statistically indistinguishable from zero, this would provide support for the common trends assumption.

An additional identification concern arises if there are heterogeneous and dynamic effects of ABLs over time. The pioneering work of Goodman-Bacon (2021) suggests that in the presence of such effects, TWFE estimates may produce biased estimates of the effects of ABL adoption on youth risky health behaviors. Moreover, event study coefficients based on TWFE estimates may

[18] Note that equations (1) and (2) are reduced form models. An alternative approach would be to generate an instrumental variables (IV) estimate of the effect of bullying victimization on risky health behaviors using adoption of a state ABL as an instrument for bullying (see, for example, Nikolaou 2017, 2022). However, there are important theoretical reasons to expect that the exclusion restriction will not be satisfied given that there are some channels through which state ABLs could directly affect risky health behaviors (not through bullying victimization) including (i) increased monitoring of student behavior by parents, teachers, and staff, or (ii) the effects of educational components of ABLs. See Rees et al. (2020) for a discussion with which we concur.

also be biased (Sun and Abraham 2021). To address this concern, we restrict the set of counterfactuals to not-yet-adopters of state ABLs (because all states adopt ABLs by 2019) and use the newly proposed estimates from Callaway and Sant'Anna (2021) to generate event study coefficients.

Third, we explore the sensitivity of estimated risky behavior effects to controls for spatial heterogeneity by estimating:

$$R_{ist} = \gamma_0 + \gamma_1 ABL_{st} + \mathbf{Z'}_{it}\,\boldsymbol{\gamma_2} + \mathbf{X'}_{st}\,\boldsymbol{\gamma_3} + \alpha_s + \pi_{rt} + \alpha_s{*}t + \mu_{ist} \quad (3)$$

where $\alpha_s{*}t$ is a state-specific linear time trend and π_{rt} is a census region-specific year effect. These controls are designed to capture unobserved geographic-specific time shocks correlated with the adoption of ABLs and with risky health behaviors. However, we note that these additional controls could increase bias in the estimated treatment effect if (i) state-specific linear time trends obscure dynamics in the true treatment effect, or (ii) states in the same census region as a treatment state serve as worse counterfactuals than states outside the census region.[19]

Finally, as noted above, we draw data on we draw data on young adults ages 18-to-25 from the National Survey of Drug Use and Health (NSDUH) to estimate the effects of ABL adoption on young adult risky health behaviors. While estimates from this sample will not produce ideal falsification tests given that there could be long-run effects of ABLs, particularly for addictive behaviors, we should not expect the effects of ABLs on these outcomes to be as large for young adults, especially in the short-run.

5. Results

Our main findings are presented in Tables 3 through 9, focusing on estimates of β_1 and γ_1.[20] All regressions are weighted using population weights generated from the SEER data to ensure the combined YRBS data are nationally representative. Standard errors are corrected for clustering on the state (Bertrand et al. 2004).

[19] See, for example, Neumark et al. (2014), Burkhauser et al. (2023) and Anderson et al. (2020) for a more detailed discussion of these issues. For instance, as Rees et al. (2022) note, state-specific trends are correlated with policies even after unobservables have been "partialled out," their inclusion could lead to "unreliable or even wrong-signed estimates" (Sheehan-Connor 2010; Hansen et al. 2017, p. 72).

[20] Coefficient estimates on the control variables are available in Appendix Table 2.

4.1 Bullying Victimization

In Panel I of Table 3, we show "first stage" estimates of the effect of state ABLs on bullying victimization. In our most parsimonious specification, which includes only state and year fixed effects and demographic controls (panel I, column 1), we find that the adoption of an ABL is associated with a 2.4 percentage-point reduction in the probability of in-school bullying victimization, or about 12 percent relative to the sample mean. This estimate is quantitatively similar to the effect size found by Rees et al. (2022). The inclusion of economic controls (column 2) and education controls (column 3) has very little effect on the estimate of β_1, with the estimate in column (3) of 0.022. This descriptive finding is consistent with the hypothesis that over this period, ABLs are adopted exogenously to bullying victimization. Moreover, we note that our "first-stage" estimate may, in fact, be a lower-bound estimate of the effectiveness of ABLs in combatting bullying to the extent that ABLs raise awareness of bullying and encourage its reporting (Sabia and Bass 2017).

In Panel II, we replace ABL_{st} with three mutually exclusive dichotomous variables: *One Wave Prior*, an indicator for whether the high school student was interviewed in the YRBS wave immediately prior to ABL adoption; *Wave of Enactment,* an indicator for whether the interview was conducted in the year of ABL adoption or the year after; and *One or More Waves After,* an indicator for whether the interview was conducted in the wave (two or more years) following ABL adoption. The reference category is composed of respondents who were interviewed two or more YRBS waves (3 or more years) prior to ABL adoption.[21] Across each of the three specifications we estimate, we find little evidence that bullying victimization differed in treatment as compared to comparison states in the wave prior to adoption. Estimated coefficients on the ABL lead range from -0.014 to -0.024 and are uniformly statistically insignificant. The absolute magnitude of the estimated effect is somewhat larger in the wave of enactment (around -0.030) and is larger still one wave or more (two years or more) following adoption (-0.040 to -0.048). This pattern of findings is consistent with ABLs leading to declines in bullying victimization rather than reflecting pre-existing bullying trends.

[21] Rees et al. (2022) discuss challenges with using years as compared to waves for event-study analysis with biennial YRBS data, writing, "Because the YRBS survey is conducted biennially, conducting an event-study analysis with one-year leads and lags is challenging. Only those states that adopted an ABL in an odd-numbered year identify the year-of-adoption effect and the effects for even-numbered years (e.g., two years before adoption), and only those states that adopted an ABL in an even-numbered year identify effects for odd-numbered years (e.g., one year before adoption)."

One concern with the YRBS survey is that it does not include information on the month in which the survey is administered. In many years, the surveys appear to have been distributed in schools during the Spring semester (January to June) but this may vary across districts (CDC 2019). To ensure that our estimated treatment effects are not contaminated by lead effects, in panel III, we recode our ABL variable by setting it equal to 1 only when the policy is in effect for the full year (to ensure that policies enacted after June are not counted as treated by surveys distributed earlier in the year). The findings in panel III are similar. Moreover, an event study analysis based on this alternative coding in Appendix Figure 1 shows a qualitatively similar pattern of findings.

In Table 4, we show the sensitivity of the first-stage estimates to the inclusion of additional controls for policies that may affect the risky health behaviors under study: tobacco control policies (cigarette tax and e-cigarette tax) in column (2), alcohol policies (beer tax) in column (3), marijuana policies (recreational and medical marijuana laws) in column (4), and school health policies (physical education requirements and sex education mandates) in column (5). Across specifications, the pattern of findings suggests that ABL adoption is associated with a 1.8-to-2.3 percentage-point reduction in the probability that a youth is bullied. Again, this pattern of findings is consistent with ABLs being adopted orthogonally to a wide set of right-hand side controls and is suggestive of a causal impact of these laws on bullying.

4.2 ABLs and Youth Risky Health Behaviors

Having documented that state ABLs reduce bullying victimization among U.S. high school students, we next turn to an exploration of whether ABLs affect risky health behaviors.[22] The first panel of Table 5 shows estimates of β_1 from equation (2). Our findings provide little support for the hypothesis that ABL adoption leads to economically meaningful or statistically significant changes in risky health behaviors for the average high school youth, as measured binge drinking (column 1), tobacco use (column 2), marijuana use (column 3), risky sexual activity (column 4), BMI (columns 5), or overweight/obese column 6). The largest (in absolute magnitude) decline in a risky health behavior is observed for binge drinking (column 1, panel I), -0.008, which could suggest an ABL-induced decline in heavier alcohol consumption, though this effect is not statistically distinguishable

[22] In Appendix Table 3, we show that the positive association between bullying victimization and risky health behaviors documented in the public health literature can be found in repeated cross-sections of the 2009-2019 YRBS surveys.

at conventional levels.[23] Overall, the estimated marginal effects in panel I of Table 5 are small and are as often positive as negatively signed.

In panel II of Table 5, we show lead and lagged effects of state ABLs on risky health behaviors. Our finding shows relatively little evidence that youth risky behaviors were trending differently in treatment and control states prior to ABL adoption, and little evidence of significant declines in any of these behaviors in the waves following adoption. The use of the alternate coding of our ABL variable (set equal to 1 only when the policy is in effect for the entire year) does not change the pattern of findings (panel III), nor does coding of the treatment using only the first two quarters of the year to define treatment (see Appendix Table 5).

How small and how precise are the estimates shown in panel III? For dichotomous outcomes, the estimated marginal effects are well under a percentage-point: 0.003 for tobacco cigarette use, 0.001 for overweight/obese, and ranging from -0.004 to -0.007 for marijuana use, binge drinking, and risky sex. Given that ABLs could be expected to affect youth risky health behaviors through a number of channels — including (i) diminished bullying victimization, (ii) increased teacher/staff monitoring of student risky behaviors, and (iii) increased parental involvement — these effects are quite small. Moreover, the precision of our estimates is such that we can rule out reasonably sized ABL-induced changes in risky health behaviors. These null results are not sensitive to the choice of control variables (see Appendix Table 6).[24,25]

Event-study analyses based on TWFE estimates are shown graphically in Figure 4. The results generally provide support for the common trends assumption and little evidence for economically important reductions in youth risky health behaviors, including in the longer run. In Figure 5, we present an alternative set of event study coefficients generated from Callaway and

[23] We return to this outcome when we explore heterogeneity in the effects of ABLs for historically marginalized sub-groups in Table 5 below. Appendix Table 4 limits the analysis sample to the years for which data on bullying victimization are available (2009-2019). The pattern of findings is qualitatively similar to those using the 1997-2019 period, though the estimated effect on binge drinking is somewhat larger, -0.011, and is now marginally significantly different from zero at conventional levels.

[24] For example, with 95 percent confidence, our estimates can rule out ABL-induced declines in risky behaviors greater than 0.7 percentage-points (2.6 percent) for overweight or obese and 1.4 percentage-points (5.8 percent) for tobacco cigarette use. With regard to binge drinking, we can rule out, with 95 percent confidence, a 1.68 percentage-point decrease in the probability of binge drinking (about 6.2 percent).

[25] Moreover, we can also rule out substantial increases in risky health behaviors associated with ABL adoption. For example, we can rule out, with 95 percent confidence, a 0.77 percentage-point increase in the probability of marijuana use (about 3.6 percent) and a 1.2 percentage-point increase in the probability of overweight or obese (or about 4.3 percent).

Sant'Anna (2021) estimates where we use not-yet-adopters of ABLs as counterfactuals.[26] Consistent with the event studies in Figure 4, event-study analyses based on Callaway and Sant'Anna (2021) estimates provide little support for the hypothesis that ABL adoption leads to economically important declines in youth risky health behaviors.

Finally, panel IV of Table 5 shows the sensitivity of the estimates in Panel I to controls for state-specific linear time trends and census region-specific year effects. The findings remain qualitatively similar. Together, the results suggest little support for the hypothesis that ABL adoption leads to important reductions in youth risky health behaviors for the average teenager.[27,28]

How do we reconcile these results with a wide body of evidence from the public health literature showing that bullying victimization is positively related to a nearly all observable risky health behaviors?[29] One interpretation is that estimates from the public health literature are not causal in nature, but rather reflect perpetrators targeting bullying victims with a higher unmeasured propensity to engage in risky health behaviors. A second interpretation is that our estimated ABL impact captures a particular local average treatment effect (LATE). This LATE does not rule out the possibility that bullying that is not affected by ABL adoption increases the propensity for risky health behaviors.

Third, it may be that ABL adoption does generate small reductions in risky health behaviors, but our estimates are insufficiently powered to detect them. With respect to this third interpretation, we provide some evidence above that our null findings are relatively precisely estimated. But a back-of-the-envelope calculation is likely also illustrative. If effects on bullying victimization were the only pathway through which ABLs could affect risky health behaviors — an assumption that is very difficult to justify given the school monitoring and parental involvement provisions of many state

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[26] As noted above, however, one concern with our dynamic difference-in-differences estimates is that they may be biased in the presence of heterogeneous and dynamic treatment effects. This problem may be especially acute because there are no never-adopters of ABLs over the sample period. Thus, previous adopters always serve as the counterfactuals for treatment states.

[27] Unweighted regressions, shown in Appendix Table 7, show a similar pattern of findings.

[28] In Appendix Table 8, we explore whether state ABLs affect substance use on school property. We find little evidence that ABLs significantly affect tobacco (column 1) or alcohol (column 2) presence on school property, but some evidence that such laws may reduce drug presence on school property (column 3). Given that there is little evidence that substance use declines among teens, this result suggests that ABLs encourage greater monitoring of student behavior on school property (and may displace some behaviors elsewhere).

[29] See, for example, Topper et al. (2011), Radliff et al. (201), Priesman et al. (2017), Case et al. (2016), Hertz et al. (2015), Holt et al. (2013), Litwiller and Brausch (2013), Roman and Taylor (2013), Puhl and King (2013), Demissie et al. (2012), and Neumark-Sztainer et al. (2002).

statutes — how large of an effect on risky health behaviors might we expect? Including lagged effects, the first-stage effects on bullying victimization are about 2-to-5 percentage-points. Thus, under the assumption that this is the only mechanism through which ABLs might affect youth health behaviors, we might expect spillovers to (dichotomous) youth risky behaviors on the order of about 1-to-2 percentage points. To this point, we note that the intent-to-treat estimates in panels I and II of Table 5 are nearly uniformly under a percentage-point and the lagged effects are often positive. While in many cases our 95 percent confidence intervals allow us to rule out declines in risky behaviors in the range of 1-to-2 percentage points, we cannot rule out that there could smaller effects on the order of 0.5-to-1.0 percentage-points (across all outcomes). However, the findings in Table 6 below suggest that even many of these small effect sizes can be ruled out when we examine ABLs with the largest bite.

4.3 Heterogeneity in ABL Effects

The remainder of the paper is spent exploring whether our null results be masking important heterogeneity in the impacts of state ABLs, particularly among vulnerable teens. In Table 6, we explore whether the effects of ABL adoption on youth risky behaviors differs by whether a stronger or weaker ABL is adopted. Consistent with Rees et al. (2023), we find that stronger state ABLs have a larger absolute impact on the probability that a youth is bullied (column 1). However, the findings in columns (2) through (7) of Table 6 provide little support for the hypothesis that more comprehensive statutes are effective at reducing risky health behaviors. Moreover, the estimated effects of stronger ABLs are now positive for binge drinking, tobacco cigarette use, and marijuana, and marijuana use. For binge drinking, we can rule out (with 95 percent confidence) strong ABL-induced declines of greater (in absolute magnitude) than 0.77 percentage-points. Moreover, we can rule out any declines in marijuana and tobacco cigarette use, where strong ABL effects are *positive* and statistically indistinguishable from zero. These findings are the strongest evidence that ABLs that drive the largest declines in bullying victimization do not lead to corresponding declines for many youth risky behaviors.

Next, in Table 7, we examine whether state ABLs are more effective in reducing risky health behaviors among a variety of demographic groups, including vulnerable teens those who have been historically marginalized. In the main, we find that the adoption of a state ABL is associated with larger declines in bullying victimization for females (row 2, column 1), Blacks (row 4, column 1) and LGBQ youth (row 8, column 1) relative to their male, non-Hispanic white, and heterosexual

counterparts, respectively.[30] For women and Blacks, who have also been found to experience disproportionate mental health gains from ABLs (Rees et al. 2022), we detect little evidence of significant declines in risky health behaviors, with estimated treatment effects that are as often (and sometimes more often) positive as negative.

Turning to heterogeneity analysis by sexual identity[31], we find that some evidence that state ABLs may have had meaningful spillover effects to risky health behaviors among LGBQ-identifying youths. For sexual minorities, we find that ABL adoption is associated with a 7.2 percentage-point (approximately 25 percent) reduction in the probability of binge drinking. These findings are consistent with Liang et al. (2023) and Rees et al. (2022), who find that LGBQ-identifying students experience among the largest psychological gains from ABL-adoption, which could reduce their need to turn to risky behaviors as a coping mechanism. The effect sizes are also sufficiently large (relative to the "first-stage" effects on victimization) that they likely reflect sexual minority-identifying students benefiting from ABL-induced increases in monitoring of their behaviors by teachers and parents.[32] Event study analyses (see Appendix Figure 2) suggests some evidence consistent with a causal interpretation of this result.

On the other hand, for heterosexual-identifying students, we find little evidence that ABL adoption is associated with significant changes in binge drinking, tobacco use, marijuana use, or risky sex. In fact, the estimated association between ABL adoption and bodyweight is significant and *positive* for heterosexual-identifying students. While one interpretation of this finding is that shielding teens from bullying-induced social pressures leads to risky behaviors (i.e., by reducing bullying of vulnerable teens based on appearance, ABLs may induce some teens may avoid healthier diet and exercise choices), an examination of event studies on heterosexual-identifiers provides little support for a causal interpretation of this finding. Thus, we conclude more modestly that ABL adoption has little effect on the risky behaviors of heterosexual-identifying teens.

[30] The respondents were asked "which of the following best describes you?" Possible outcomes included "heterosexual, gay or lesbian, bisexual, or not sure." We code an individual as LGBQ youth if he/she responds gay or lesbian, bisexual, or not sure.

[31] We note that consistent asking of questions about sexual identity of teens are only available for the period 2009-2019, with an increasing number of states asking students about their sexual identity through the 2019 wave.

[32] In results reported in Appendix Table 9, we find no evidence that ABL adoption affects the likelihood that a teen identifies as LGBQ.

4.3 NSDUH Sensitivity Analysis

In panels I through IV of Table 8, we explore the sensitivity of our above YRBSS estimates to the use of the NSDUH. Our findings provide little support for the hypothesis that ABL adoption is associated with statistically significant or economically important declines in binge drinking (column 1), marijuana use (column 2), or illicit drug use other than marijuana (column 3). The estimated treatment effects in Panel I uniformly fail to show significant declines in substance use, and we can rule out, with 95 percent confidence, binge drinking declines of greater than 0.5 percentage-points for binge drinking, 0.6 percentage-points for marijuana use, and 0 percentage-points for illicit drug use other than marijuana (where we detect a significant positive coefficient). The use of stronger or weaker ABLs (panel II) and additional controls for spatial heterogeneity (panel III) does not change our pattern of null findings.

In panel IV, we turn to young adults ages 18-to-25, an age demographic that is expected to be much less affected by ABLs, except through longer-run impacts through individuals having had their risky behavior trajectories changed while in high school. The findings in panel IV show that ABL adoption is associated with a (statistically insignificant) 0.04 percentage-point increase in binge drinking, a 0.2 percentage-point increase in marijuana use, and a (marginally significant) 0.4 percentage-point increase in illicit drug use other than marijuana. We conclude that there is little evidence that ABLs affect risky behaviors of young adults.

4.4 Cyberbullying

Social psychologists have recently debated the relative health effects of traditional bullying as compared to cyberbullying. Cyberbullying is defined by the U.S. Department of Health and Human Services as,

> "…bullying that takes place over digital devices like cell phones, computers, and tablets. Cyberbullying can occur through SMS, Text, and apps, or online in social media, forums, or gaming where people can view, participate in, or share content. Cyberbullying includes sending, posting, or sharing negative, harmful, false, or mean content about someone else. It can include sharing personal or private information about someone else causing embarrassment or humiliation." (U.S. Department of Health and Human Services 2019)

While cyberbullying rarely occurs independently of traditional bullying (Waasdorp and Bradshaw 2015; Centers for Disease Control and Prevention 2017), some anti-bullying advocates have argued that the psychological impacts of cyberbullying may be greater. This may be due to increased

potential "for a large audience," "for anonymous bullying," "less supervision," and "decreased time and space limits" (Sticca and Perren 2013). On the other hand, traditional bullying, which can include physical intimidation, violence, and theft, may also have substantial adverse health effects (Rees et al. 2020). In fact, a number of studies have found that cyberbullying may cause *less* psychological harm than traditional bullying (Ortega et al. 2012; Hase et al. 2015; Rees et al. 2020).

In Table 9, we present estimates of the effects of anti-cyberbullying laws (ACBLs) on cyberbullying victimization and risky health behaviors. Panel I examines the period from 2011 through 2019 when there were data on cyberbullying, defined as having "ever been electronically bullied, during the past 12 months." In the YRBS sample, 15.7 percent of high school students were victims of cyberbullying. Following Nikolaou (2017; 2020), an ACBL is defined as a state-level policy aimed at preventing cyberbullying through an increase of awareness of cyberbullying severity as well as the costs of cyberbullying.

In columns (1) and (2) of Table 9, we fail to find evidence that ACBLs were associated with declines in cyberbullying (2011-2019) or traditional bullying (2009-2019). We also fail to detect any evidence that ABL adoption affects risky health behaviors. In the latter case, our estimates are obtained with sufficient precision such that we can rule out (with 95 percent confidence) ACBL-induced reductions in the probabilities of binge drinking of 1.5 percentage-points, tobacco use of 3.4 percentage-points, and overweight or obesity of 1.4 percentage-points.

6. Conclusions

Federal policymakers, public health researchers, and the National Academies of Sciences, Engineering, and Medicine have argued for a broad public health approach to reduce bullying in schools. This recommendation is owed, in part, to a wide epidemiological literature that has concluded "probable evidence" of a causal relationship between bullying victimization and a wide set of risky health behaviors. However, the empirical methods used in these studies have made it difficult to disentangle the causal effect of bullying victimization from non-random targeting of victims based on difficult-to-measure traits associated with risky health behaviors.

This study circumvents these empirical challenges by exploiting geographic and temporal variation in the adoption of state ABLs to identify their effect on risky health behaviors. We find that while ABLs — particularly more comprehensive statutes — are effective at reducing bullying victimization, they do little to reduce a wide set of risky health behaviors for the average U.S. high school student. The estimated relationships between state ABLs and risky health behaviors are, in

the main, economically small and are uniformly statistically indistinguishable from zero at conventional levels.

When we turn to demographic subgroups, for LGBQ-identifying teenagers, we find that ABL-adoption is associated with a significant (and large) reduction in binge drinking. These findings are consistent with prior evidence that LGBQ students experienced the largest psychological health gains from ABLs and appear to have reduced engaging in some risky health behaviors as a coping mechanism.

In the main, the results of this study suggest that the margin of bullying victimization reduced by ABLs likely generates, at most, only small declines in youth risky behaviors for the average teenager. However, is important to put our null findings on risky behaviors (for the average teen) in the context of the broader literature on the impacts of ABLs. Recent studies point to important psychological benefits that flow from ABL adoption, including a reduction in suicidal behaviors (Rees et al. 2022; Liang et al. 2023; Nikolaou 2017) and depression (Rees et al. 2022). There is also evidence that ABL adoption may improve school safety (Sabia and Bass 2017), reduce school shootings (Sabia and Bass 2017), and prevent teenage suicide (Rees et al. 2022). These effects may generate important human capital-related social benefits. Rather, we cast our (largely) null findings as more of a splash of "cold water" on assertions by public health advocates that typical policy strategies to fight bullying would generate a broad-based reduction in risky health behaviors for the average teenager.

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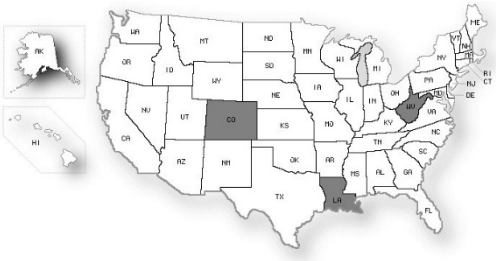
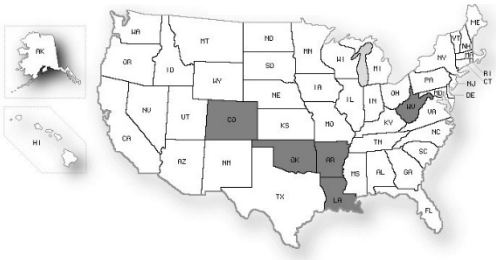
Figure 1. Enactment of State ABLs, 1997-2019

1997

2001



2003



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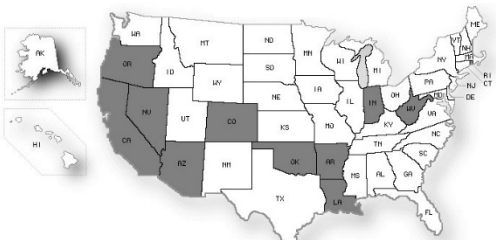
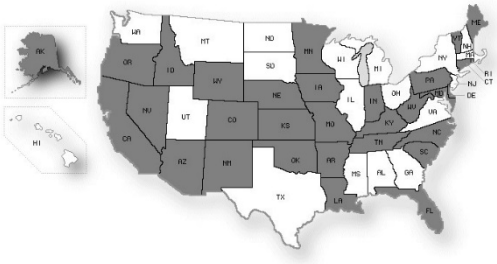
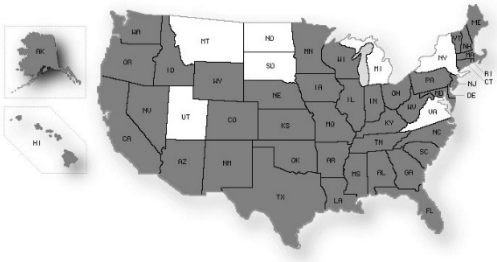


2007

2009



2011



2013

2019

Sources: Sabia and Bass (2017), Rees et al. (2020)

Figure 2. Bullying Victimization and Substance Use Among U.S. High School Students, 1997-2019

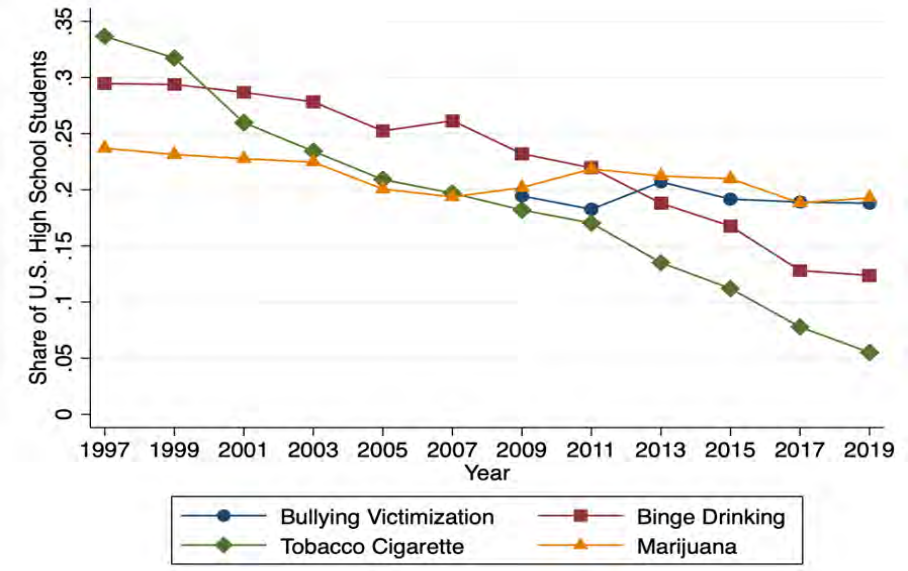


Figure 3. Risky Sexual Activity and Body Weight Among U.S. High School Students, 1997-2019

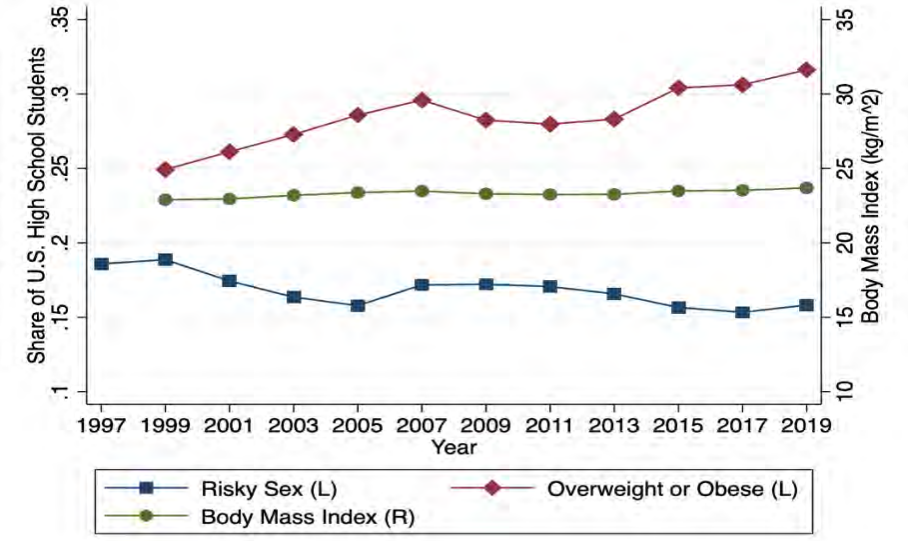
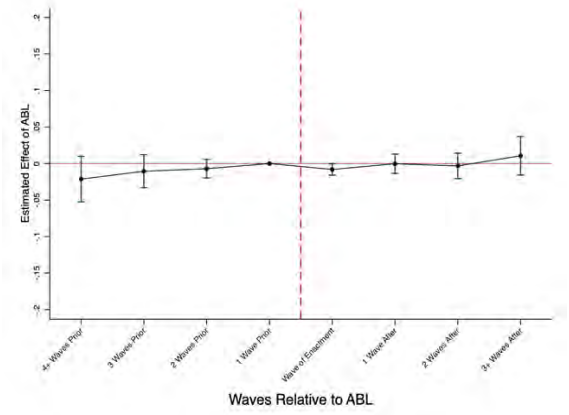
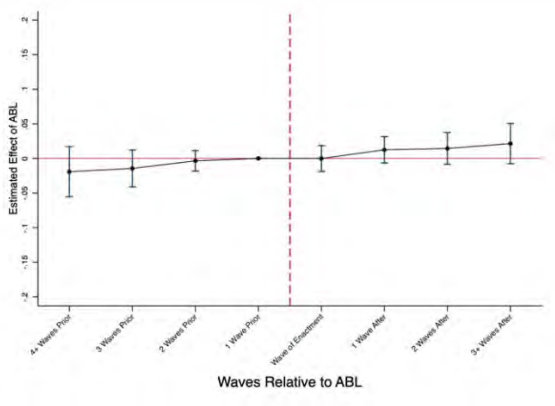


Figure 4. Event-Study Analyses of ABLs and Risky Health Behaviors, Using TWFE Estimates

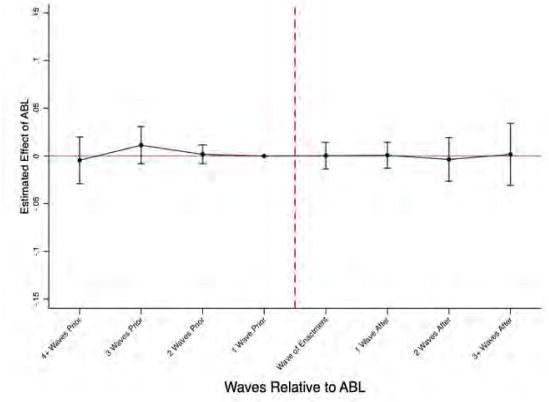
Panel (a): Binge Drinking



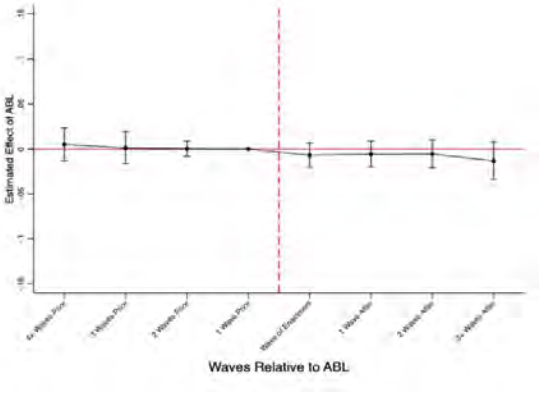
Panel (b): Tobacco Cigarette



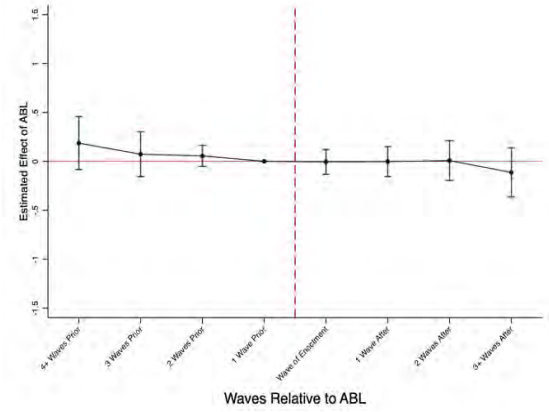
Panel (c): Marijuana Use



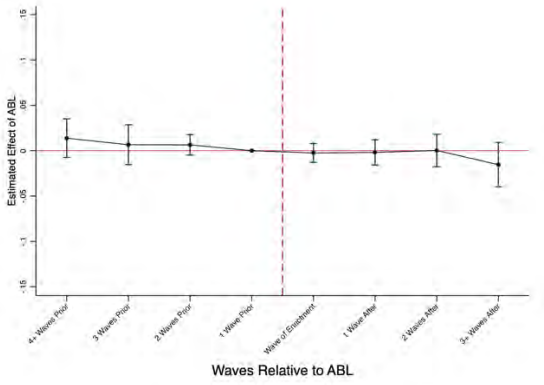
Panel (d): Risky Sex



Panel (e): BMI

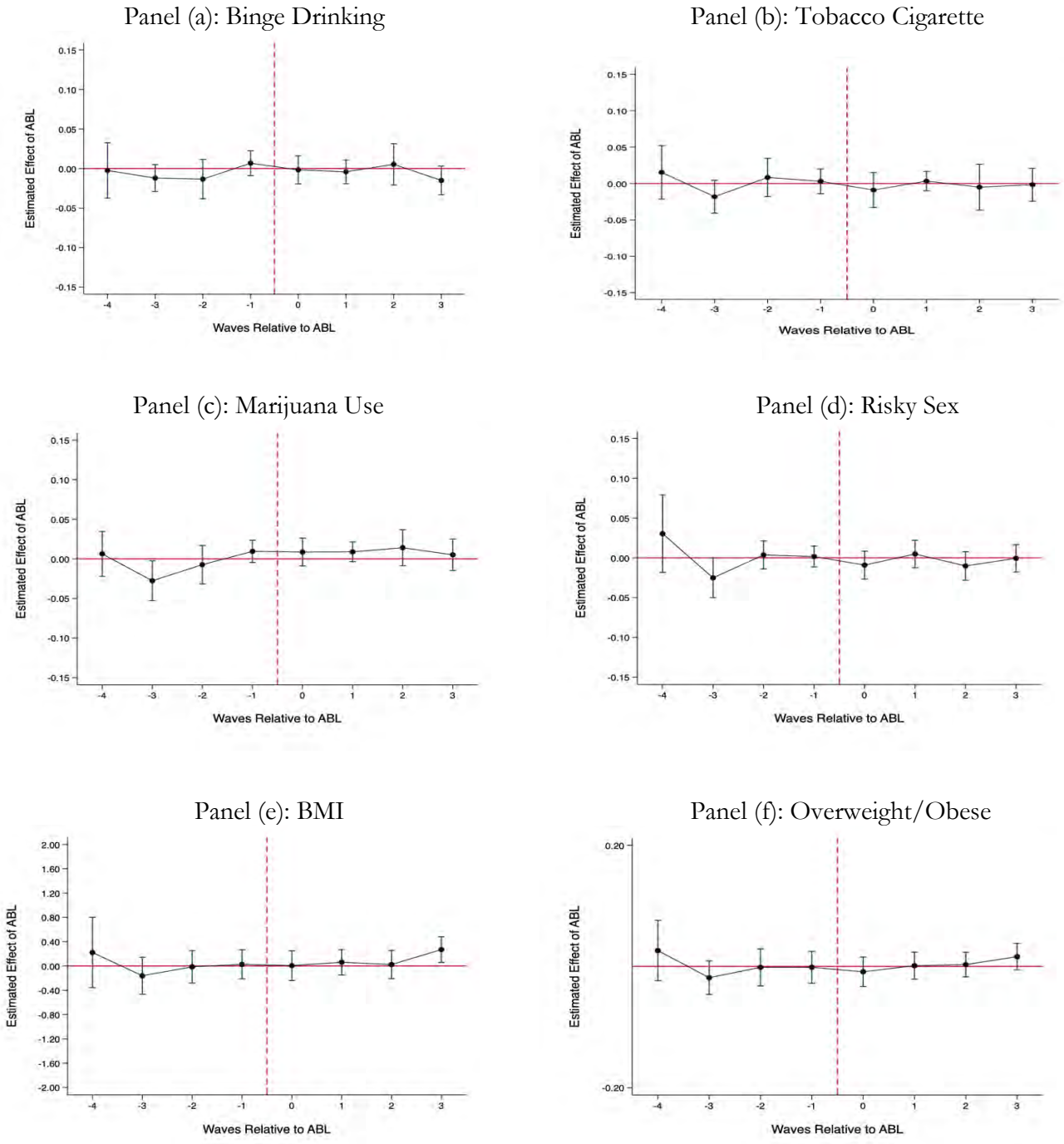


Panel (f): Overweight/Obese



Notes: Estimated marginal effects are obtained using weighted OLS regression with data from the 1997 to 2019 Youth Risk Behavior Surveys. All regressions include state and year fixed effects and all controls listed in Column 6 of Table 4. Vertical lines show the 95 percent confidence intervals and the dotted vertical line shows ABL enactment. The reference category is one wave prior to enactment of an ABL. All regressions include survey YRBS fixed effects.

Figure 5. Event-Study Analyses of Effect of State ABLs on Risky Health Behaviors, Callaway and Sant'Anna (2021) Estimates



Notes: Estimated marginal effects are obtained using Callaway and Sant'Anna estimator with data from the 1997 to 2019 Youth Risk Behavior Surveys. All regressions control for average age, sex, Hispanics and Blacks population. Vertical lines show the 95 percent confidence intervals and the dotted vertical line shows ABL enactment.

Table 1. Effective Dates of State Anti-Bullying Laws

State	Effective Date	State	Effective Date
Alabama	July 1, 2010	Montana	April 21, 2015
Alaska	July 1, 2007	Nebraska	July 1, 2009
Arizona	August 12, 2005	Nevada	July 1, 2005
Arkansas	July 16, 2003	New Hampshire[s]	January 1, 2011
California	January 1, 2004	New Jersey[s]	September 1, 2011
Colorado	August 8, 2001	New Mexico	April 1, 2007
Connecticut[s]	February 1, 2009	New York	July 1, 2013
D.C.	June 22, 2012	North Carolina	December 31, 2009
Delaware[s]	January 1, 2008	North Dakota	July 1, 2012
Florida[s]	December 1, 2008	Ohio	September 29, 2010
Georgia	August 1, 2011	Oklahoma	November 1, 2002
Hawaii[s]	July 11, 2011	Oregon	January 1, 2004
Idaho	July 1, 2006	Pennsylvania	January 1, 2009
Illinois	June 28, 2010	Rhode Island	September 1, 2004
Indiana	July 1, 2005	South Carolina	January 1, 2007
Iowa	September 1, 2007	South Dakota	January 1, 2012
Kansas	July 1, 2008	Tennessee	January 1, 2006
Kentucky	November 30, 2008	Texas	June 17, 2011
Louisiana	August 1, 2001	Utah	September 1, 2012
Maine	September 1, 2006	Vermont[s]	January 15, 2007
Maryland[s]	July 1, 2009	Virginia	July 1, 2013
Massachusetts	December 31, 2010	Washington[s]	August 1, 2011
Michigan[s]	June 7, 2012	West Virginia	December 1, 2001
Minnesota	August 1, 2007	Wisconsin	August 15, 2010
Mississippi	December 31, 2010	Wyoming	December 31, 2009
Missouri	September 1, 2007		

Sources: Sabia and Bass (2017), Rees et al. (2020)
[s]Stronger ABL

Table 2. Descriptive Statistics

	Full	ABL=1[α]	ABL=0	N	Description
Dependent Variables					
YRBS Outcomes					
Bullying Victimization	.192	.191	.201	939,189	= 1 if respondent had been bullied on school property in the
	(.394)	(.393)	(.401)		last 12 months, = 0 otherwise
Cyber-Bullying Victimization	0.147	0.147	0.158	895,900	= 1 if respondent had been electronically bullied in the
	(0.354)	(0.354)	(0.365)		last 12 months, = 0 otherwise
Binge Drinking	.226	.184	.272	1,402,124	= 1 if respondent consumed more than 5 alcoholic beverages at
	(.418)	(.387)	(.445)		one time in the past 30 days, = 0 otherwise
Tobacco Cigarette	.185	.127	.251	1,471,042	= 1 if respondent has smoked cigarettes in the past 30 days, = 0
	(.389)	(.333)	(.434)		otherwise
Marijuana	.210	.204	.218	1,497,685	= 1 if respondent has smoked marijuana in the past 30 days, =
	(.408)	(.403)	(.412)		0 otherwise
Risky Sex	.168	.162	.174	1,289,816	= 1 if respondent did not use a condom the last time they had
	(.373)	(.369)	(.379)		sexual intercourse, = 0 otherwise
BMI	23.31	23.42	23.18	1,360,976	= weight (kg) / height $(m)^2$
	(4.88)	(4.99)	(4.72)		
Overweight or Obese	.285	.295	.273	1,360,976	= 1 if respondent's BMI is at or above the 85^{th} percentile, = 0
	(.452)	(.456)	(.445)		otherwise
Tobacco Cigarette Use	0.071	0.047	0.087	624,871	= 1 if respondent has smoked cigarettes in the past 30 days on
On School Property	(0.257)	(0.212)	(0.281)		school property, = 0 otherwise
Binge Drinking	0.047	0.043	0.049	659,942	= 1 if respondent consumed more than 5 alcoholic beverages at
On School Property	(0.211)	(0.203)	(0.215)		one time in the past 30 days on school property, = 0 otherwise
Drug Presence	0.256	0.243	0.272	1,229,701	= 1 if respondent were offered, sold or given an illegal drug on
On School Property	(0.437)	(0.429)	(0.445)		school property, = 0 otherwise
NSDUH Outcomes (State-Level)					

Marijuana Use, Ages 12-to-17	0.074 (0.017)	0.074 (0.017)	0.075 (0.016)	765	= proportion of 12-to-17-year-olds using marijuana at least once in the past month
Marijuana Use, Ages 18-to-25	0.187 (0.050)	0.194 (0.052)	0.173 (0.042)	765	= proportion of 18-to-25-year-olds using marijuana at least once in the past month
Binge Drinking, Ages 12-to-17	0.087 (0.025)	0.076 (0.020)	0.105 (0.023)	714	= proportion of 12-to-17-year-olds binge drinking at least once in the past month
Binge Drinking, Ages 18-to-25	0.418 (0.064)	0.406 (0.057)	0.437 (0.071)	714	= proportion of 18-to-25-year-olds binge drinking at least once in the past month
Illicit Drug Use Other than MJ, Ages 12-to-17	0.043 (0.011)	0.039 (0.011)	0.049 (0.008)	714	= proportion of 12-to-17-year-olds using illicit drugs other than MJ at least once in the past month
Illicit Drug Use Other than MJ, Ages 18-to-25	0.080 (0.016)	0.079 (0.017)	0.081 (0.014)	714	= proportion of 18-to-25-year-olds using illicit drugs other than MJ at least once in the past month
Independent Variables					
ABL	.505 (.491)	.957 (.152)	0 (0)	1,497,685	= 1 if state has enacted an anti-bullying law, = 0 otherwise
Weaker ABL	.425 (.487)	.805 (.377)	0 (0)	1,497,685	= 1 if state has enacted a weaker anti-bullying law, = 0 otherwise
Stronger ABL	.080 (.269)	.152 (.355)	0 (0)	1,497,685	= 1 if state has enacted a stronger anti-bullying law, = 0 otherwise
ACBL	0.476 (0.493)	0.858 (0.337)	0.049 (0.206)	1,497,685	= 1 if state has enacted an anti-cyberbullying law, = 0 otherwise
Male	.512 (.500)	.508 (.500)	.513 (.500)	1,497,685	= 1 if respondent is male, = 0 if female
White	.590 (.492)	.554 (.497)	.631 (.483)	1,497,685	= 1 if respondent is non-Hispanic white, = 0 otherwise
Hispanic	.203 (.402)	.238 (.426)	.165 (.371)	1,497,685	= 1 if respondent is Hispanic, = 0 otherwise
Black	.148 (.356)	.142 (.349)	.156 (.363)	1,497,685	= 1 if respondent is black, = 0 otherwise
Other Race	.058 (.0234)	0.067 (.250)	.049 (.215)	1,497,685	= 1 if respondent is not white, Hispanic or black, = 0 otherwise
Age	16.02 (1.41)	16.02 (1.41)	16.01 (1.41)	1,497,685	= age of respondent

Unemployment	.058	.062	.054	1,497,685	= state unemployment rate
	(.021)	(.024)	(.016)		
Income per capita	4.02	4.64	3.33	1,497,685	= state income per capita per thousand
	(1.03)	(.886)	(.70)		
Bachelor's degree	.296	.319	.271	1,497,685	= state hare of population with bachelor's degree
	(.056)	(.054)	(.045)		
Pupil/teacher ratio	16.37	16.75	15.95	1,497,685	= state average pupil/teacher ratio
	(3.04)	(3.38)	(2.53)		
Teacher salary	5.09	5.53	4.61	1,497,685	= state average teacher salary per thousand
	(1.07)	(1.07)	(.846)		
Cigarette Tax	.997	1.35	.601	1,497,685	= state per-pack cigarette tax (2019 dollars)
	(.910)	(.982)	(.615)		
E-cigarette Tax	.039	.074	0	1,497,685	= state per fluid mL e-cigarette tax (2019 dollars)
	(.237)	(.322)	(0)		
Beer Tax	.228	.259	.193	1,497,685	= state per-ounce beer tax (2019 dollars)
	(.233)	(.270)	(.178)		
Medical Marijuana Law	.282	.456	.087	1,497,685	= 1 if state has enacted a medical marijuana law, = 0 otherwise
	(.448)	(.494)	(.281)		
Recreational Marijuana Law	.042	.079	0	1,497,685	= 1 if state has enacted a recreational marijuana law, = 0 otherwise
	(.200)	(.269)	(0)		
Sex Education Requirement	.329	.357	.298	1,497,685	= 1 if state has mandated sex education, = 0 otherwise
	(.470)	(.479)	(.457)		
PE Credit Requirements	1.06	1.02	1.09	1,497,685	= state physical education credits required for graduation
	(.870)	(.825)	(.918)		

Notes: Weighted means with standard deviations in parenthesis.
¤ Observations in state-year with partial ABLs are included in ABL=1.

Table 3. TWFE Estimates of Relationship Between Anti-Bullying Laws and Bullying Victimization, 2009-2019

	(1)	(2)	(3)
		Panel I: Baseline TWFE	
ABL	-0.024[b]	-0.024[b]	-0.022[b]
	(0.011)	(0.011)	(0.010)
		Panel II: Lead and Lagged Effects	
One Wave Prior to ABL	-0.014	-0.017	-0.024
	(0.019)	(0.017)	(0.016)
Wave of ABL Enactment	-0.025	-0.029	-0.032[c]
	(0.021)	(0.019)	(0.018)
One or More Waves After ABL	-0.040	-0.043[c]	-0.048[b]
	(0.024)	(0.022)	(0.021)
		Panel III: Alternate ABL coding (ABL = 1 if in effect for full year; = 0 otherwise)	
ABL	-0.019[b]	-0.019[b]	-0.017[b]
	(0.009)	(0.008)	(0.008)
State and Year FE?	Yes	Yes	Yes
Demographic Controls?	Yes	Yes	Yes
Economic Controls?	No	Yes	Yes
Education Controls?	No	No	Yes
Pre-Treatment Mean of DepVar	0.201	0.201	0.201
N	939,189	939,189	939,189

[a]Significant at 1% level, [b]5% level, [c]10% level

Notes: Estimated marginal effects are obtained using weighted OLS regression with data from the Youth Risk Behavior Surveys. Standard errors corrected for clustering on the state are in parentheses. In the results shown in Panel II, the reference category is two or more waves prior to enactment of an ABL. Demographic controls include gender, age, grade, and race/ethnicity. Economic controls include state unemployment rate, per capita income, and share of population with bachelor's degree. Education controls include average teacher salary, and average pupil/teacher ratio. All regressions include survey YRBS fixed effects.

Table 4. Sensitivity of Bullying Victimization Effects to Additional Controls Related to Risky Health Behaviors, 2009-2019

	(1)	(2)	(3)	(4)	(5)	(6)
ABL	-0.022[b]	-0.018[c]	-0.023[b]	-0.022[b]	-0.021[b]	-0.018[c]
	(0.01)	(0.010)	(0.01)	(0.010)	(0.011)	(0.010)
State and Year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Column (3), Table 3 Controls	Yes	Yes	Yes	Yes	Yes	Yes
Tobacco Policy Controls?	No	Yes	No	No	No	Yes
Alcohol Policy Controls?	No	No	Yes	No	No	Yes
Marijuana Policy Controls?	No	No	No	Yes	No	Yes
School Health Policy Controls?	No	No	No	No	Yes	Yes
Pre-Treatment Mean of DepVar	0.201	0.201	0.201	0.201	0.201	0.201
N	939,189	939,189	939,189	939,189	939,189	939,189

[a]Significant at 1% level, [b]5% level, [c]10% level

Notes: Estimated marginal effects are obtained using weighted OLS regression with data from the Youth Risk Behavior Surveys. Standard errors corrected for clustering on the state are in parentheses. Tobacco policy controls include the state cigarette tax and e-cigarette tax, alcohol policy controls include the state beer tax, marijuana policy controls include medical and recreational marijuana laws, and school health policy controls include sex education and physical education requirement laws. All regressions include survey YRBS fixed effects.

Table 5. Estimates of Relationship Between Anti-Bullying Laws and Risky Health Behaviors, 1997-2019

	(1)	(2)	(3)	(4)	(5)	(6)
	Binge Drinking	**Tobacco Cigarette**	**Marijuana**	**Risky Sex**	**Body Mass Index**	**Overweight or Obese**
			Panel I: TWFE			
ABL	-0.008	0.005	-0.006	-0.006	0.026	-0.0004
	(0.006)	(0.011)	(0.007)	(0.007)	(0.074)	(0.005)
			Panel II: Lead and Lagged Effects			
5+ Wave Prior	-0.018	0.011	0.001	-0.012	0.061	-0.005
	(0.016)	(0.018)	(0.012)	(0.012)	(0.133)	(0.012)
4 Waves Prior	-0.023[c]	-0.015	-0.010	-0.002	0.105	0.0022
	(0.013)	(0.017)	(0.010)	(0.010)	(0.119)	(0.011)
3 Waves Prior	-0.016	-0.012	0.009	-0.005	0.101	0.005
	(0.012)	(0.015)	(0.010)	(0.011)	(0.153)	(0.015)
2 Waves Prior	-0.005	-0.004	0.004	-0.006	0.086	0.008
	(0.007)	(0.006)	(0.006)	(0.006)	(0.055)	(0.006)
1 Wave Prior	-	-	-	-	-	-
Wave of Enactment	-0.010	-0.006	-0.0009	-0.007	0.042	0.003
	(0.006)	(0.013)	(0.010)	(0.009)	(0.079)	(0.007)
1 Wave After	-0.005	-0.004	-0.006	-0.008	0.065	0.004
	(0.007)	(0.010)	(0.007)	(0.008)	(0.076)	(0.007)
2 Waves After	-0.0004	0.008	0.001	0.002	0.072	0.011
	(0.010)	(0.013)	(0.014)	(0.010)	(0.098)	(0.009)
3+ Waves After	0.006	0.0023	-0.0006	-0.006	-0.001	-0.0003
	(0.014)	(0.014)	(0.017)	(0.010)	(0.120)	(0.011)
			Panel III: Alternate ABL coding (ABL = 1 if in effect for full year; = 0 otherwise)			
ABL	-0.007	0.003	-0.004	-0.004	0.026	0.001
	(0.005)	(0.009)	(0.006)	(0.006)	(0.063)	(0.004)

	Panel IV: Additional Controls for State-Specific Linear Time Trends and Census Region-Specific Year Fixed Effects					
ABL	-0.011	-0.004	-0.006	-0.008	0.056	0.0021
	(0.006)	(0.008)	(0.006)	(0.006)	(0.055)	(0.005)
Pre-Treatment Mean of Dep Var	0.272	0.251	0.218	0.174	23.18	0.273
N	1,402,124	1,471,042	1,497,685	1,289,816	1,360,976	1,360,976

[a]Significant at 1% level, [b]5% level, [c]10% level

Notes: Estimated marginal effects are obtained using weighted OLS regression with data from the Youth Risk Behavior Surveys. Standard errors corrected for clustering on the state are in parentheses. In the results shown in Panel II, the reference category is two or more waves prior to enactment of an ABL. All regressions include state and year fixed effects and controls for gender, age, grade, race/ethnicity, state unemployment rate, per capita income, share of population with bachelor's degree, average teacher salary, average pupil/teacher ratio, physical education credit requirements, sex education mandates, cigarette taxes, e-cigarette taxes, beer taxes, medical marijuana laws, and recreational marijuana laws. All regressions include survey YRBS fixed effects.

Table 6. Heterogeneity in Effects of Anti-Bullying Laws, by Strength of Statute

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Bullying Victimization	**Binge Drinking**	**Tobacco Cigarette**	**Marijuana**	**Risky Sex**	**Body Mass Index**	**Overweight or Obese**
Stronger ABL	-0.032[b]	0.008	0.025 [b]	0.020[a]	-0.007	-0.055	-0.004
	(0.012)	(0.008)	(0.012)	(0.007)	(0.008)	(0.113)	(0.010)
Weaker ABL	-0.013	-0.010[c]	0.002	-0.009	-0.006	0.039	0.0003
	(0.013)	(0.006)	(0.012)	(0.007)	(0.007)	(0.075)	(0.005)
Pre-Treatment Mean	0.201	0.272	0.251	0.218	0.174	23.18	0.273
N	939,189	1,402,124	1,471,042	1,497,685	1,289,816	1,360,976	1,360,976

[a]Significant at 1% level, [b]5% level, , [c]10% level

Notes: Estimated marginal effects are obtained using weighted OLS regression with data from the Youth Risk Behavior Surveys. Standard errors corrected for clustering on the state are in parentheses. All regressions include state and year fixed effects and controls for gender, age, grade, race/ethnicity, state unemployment rate, per capita income, share of population with bachelor's degree, average teacher salary, average pupil/teacher ratio, physical education credit requirements, sex education mandates, cigarette taxes, e-cigarette taxes, beer taxes, medical marijuana laws, and recreational marijuana laws. All regressions include survey YRBS fixed effects.

Table 7. Heterogeneity in Effects of Anti-Bullying Laws, by Demographic Group, 1997-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Bullying Victimization	**Binge Drinking**	**Tobacco Cigarette**	**Marijuana**	**Risky Sex**	**BMI**	**Overweight or Obese**
Males	-0.015	-0.009	0.006	-0.009	-0.017[b]	-0.022	-0.008
	(0.011)	(0.009)	(0.013)	(0.010)	(0.008)	(0.069)	(0.005)
Pre-Treat Mean DV	0.196	0.293	0.258	0.248	0.153	23.57	0.312
N	458195	680346	713616	726937	613830	670041	670041
Females	-0.021	-0.007	0.004	-0.002	0.005	0.074	0.007
	(0.013)	(0.005)	(0.011)	(0.006)	(0.008)	(0.104)	(0.008)
Pre-Treat Mean DV	0.206	0.249	0.244	0.186	0.196	22.76	0.230
N	480994	721778	757426	770748	675986	690935	690935
Non-Hisp Whites	-0.015	-0.011	0.002	-0.010	-0.008	-0.102	-0.012
	(0.011)	(0.008)	(0.012)	(0.007)	(0.008)	(0.076)	(0.008)
Pre-Treat Mean DV	0.223	0.308	0.286	0.219	0.162	22.81	0.243
N	491375	791373	834027	850577	748403	775492	775492
Blacks	-0.029[c]	-0.003	-0.011	0.005	-0.011	0.255	0.008
	(0.015)	(0.01)	(0.012)	(0.01)	(0.008)	(0.208)	(0.018)
Pre-Treat Mean DV	0.150	0.130	0.143	0.216	0.194	24.15	0.343
N	139415	206384	208090	208964	164943	188544	188544
Ages 14-to-16	-0.012	-0.005	-0.002	0.001	0.001	-0.020	0.0001
	(0.011)	(0.004)	(0.004)	(0.004)	(0.004)	(0.047)	(0.004)
Pre-Treat Mean DV	0.236	0.220	0.205	0.185	0.118	22.76	0.285
N	631672	915283	962052	977203	840044	885394	885394
Age 17-to-18	-0.012	-0.003	-0.001	0.007	-0.009	0.055	0.0002
	(0.012)	(0.007)	(0.006)	(0.006)	(0.006)	(0.093)	(0.007)
Pre-Treat Mean DV	0.151	0.344	0.303	0.263	0.251	23.86	0.259
N	308466	472820	495292	506535	436165	461888	461888
Heterosexuals	-0.021[b]	-0.004	0.008	0.01	-0.004	0.266[c]	0.028[a]
	(0.009)	(0.011)	(0.005)	(0.011)	(0.009)	(0.145)	(0.010)
Pre-Treat Mean DV	0.175	0.241	0.157	0.218	0.165	23.21	0.264
N	473316	463538	530512	534640	484869	510466	510466
Sexual Minorities (LGBQ)	-0.083[b]	-0.072[b]	0.012	0.040	0.020	0.242	-0.001
	(0.040)	(0.034)	(0.022)	(0.028)	(0.035)	(0.289)	(0.029)
	0.395	0.288	0.281	0.310	0.300	24.17	0.356
N	75917	72108	82992	83734	71352	78410	78410

[a]Significant at 1% level, [b]5% level , [c]10% level

Notes: Estimated marginal effects are obtained using weighted OLS regression with data from the Youth Risk Behavior Surveys. Standard errors corrected for clustering on the state are in parentheses. All regressions include state and year fixed effects and controls for gender, age, grade, race/ethnicity, state unemployment rate, per capita income, share of population with bachelor's degree, average teacher salary, average pupil/teacher ratio, physical education credit requirements, sex education mandates, cigarette taxes, e-cigarette taxes, beer taxes, medical marijuana laws, and recreational marijuana laws. All regressions include survey YRBS fixed effects. The analysis on heterosexual and sexual minorities are conducted on state YRBS for the period 2009-2019, when data on sexual identify are consistently provided.

Table 8. Robustness of Estimates to Use of the National Survey on Drug Use and Health

	(1)	(2)	(3)
	Binge Drinking	**Marijuana Use**	**Illicit Drug Use Other than MJ**
	Panel I: ABL Effects, Ages 12-to-17		
ABL	-0.001	-0.002	0.002[b]
	(0.002)	(0.002)	(0.0009)
	Panel II: ABL Effects, by Strength of Statute, Ages 12-to-17		
Stronger ABL	0.002	0.004	0.001
	(0.003)	(0.003)	(0.001)
Weaker ABL	-0.002	-0.003	0.002[a]
	(0.002)	(0.002)	(0.001)
	Panel III: Additional Controls for State-Specific Linear Time Trends and Census Region-Specific Year Fixed Effects		
ABL	0.002	-0.0006	0.002[b]
	(0.002)	(0.002)	(0.001)
Pre-Treat Mean DV	0.105	0.075	0.049
	Panel IV: TWFE. Ages 18-to-25		
ABL	0.0004	0.002	0.004[c]
	(0.005)	(0.005)	(0.002)
Pre-Treat Mean DV	0.437	0.173	0.081
N	714	765	714

[a]Significant at 1% level, [b]5% level , [c]10% level

Notes: Estimated marginal effects are obtained using weighted OLS regression with data from the National Survey on Drug Use and Health. Standard errors corrected for clustering on the state are in parentheses. All regressions include state and year fixed effects and age specific controls for state proportions of males, Whites, Blacks, Hispanics and other races, and state average age. The model also includes state unemployment rate, per capita income, share of population with bachelor's degree, average teacher salary, average pupil/teacher ratio, physical education credit requirements, sex education mandates, cigarette taxes, e-cigarette taxes, beer taxes, medical marijuana laws, and recreational marijuana laws.

Table 9. Estimates of Relationship Between Anti-Cyber Bullying Laws (ACBLs) and Risky Health Behaviors

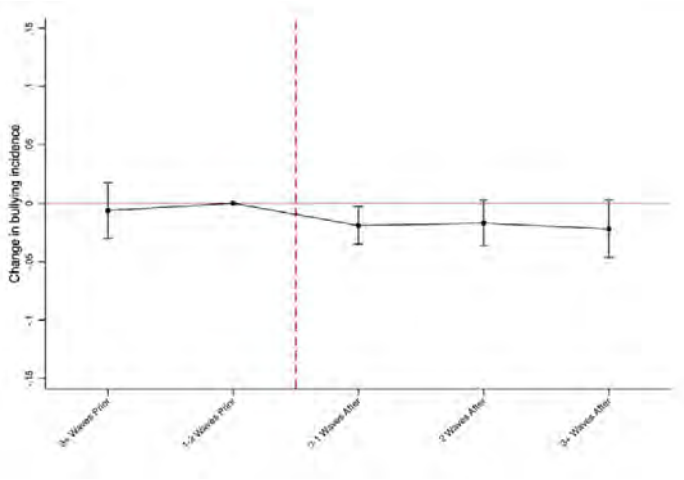
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	E-Bullying Victimization	**Bullying Victimization**	**Binge Drinking**	**Tobacco Cigarette**	**Marijuana**	**Risky Sex**	**Overweight or Obese**
ACBL	-0.007	0.001	0.001	-0.014	0.002	-0.005	-0.004
	(0.013)	(0.010)	(0.008)	(0.010)	(0.008)	(0.005)	(0.005)
Pre-Treat Mean DV	0.158	0.201	0.272	0.251	0.218	0.174	0.273
N	894647	939189	1402124	1471042	1497685	1289816	1360976

[a]Significant at 1% level, [b]5% level

Notes: Estimated marginal effects are obtained using weighted OLS regression with data from the Youth Risk Behavior Surveys. Standard errors corrected for clustering on the state are in parentheses. All regressions include state and year fixed effects and controls for gender, age, grade, race/ethnicity, state unemployment rate, per capita income, share of population with bachelor's degree, average teacher salary, average pupil/teacher ratio, physical education credit requirements, sex education mandates, cigarette taxes, e-cigarette taxes, beer taxes, medical marijuana laws, and recreational marijuana laws.

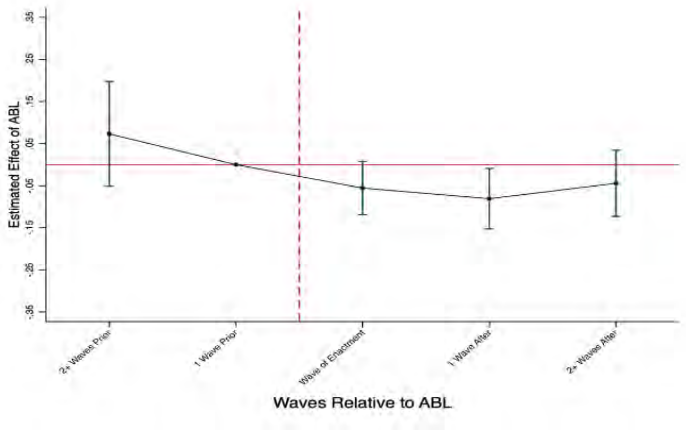
Online Appendix Figures and Tables

Appendix Figure 1. Event-Study Analyses of ABLs and Bullying Victimization, Using TWFE Estimates



Notes: Estimated marginal effects are obtained using weighted OLS regression with data from the 1997 to 2019 Youth Risk Behavior Surveys. All regressions include state and year fixed effects and all controls listed in Column 6 of Table 4. Vertical lines show the 95 percent confidence intervals and the dotted vertical line shows ABL enactment. The reference category is one wave prior to enactment of an ABL. All regressions include survey YRBS fixed effects.

Appendix Figure 2. Event-Study Analyses of ABLs and Binge Drinking, for LGBQ-Identifying Individuals, Using TWFE Estimates



Notes: Estimated marginal effects are obtained using weighted OLS regression with data from the 2009 to 2019 state Youth Risk Behavior Surveys. All regressions include state and year fixed effects and all controls listed in Column 3 of Table 3. Vertical lines show the 95 percent confidence intervals and the dotted vertical line shows ABL enactment. The reference category is one wave prior to enactment of an ABL. All regressions include survey YRBS fixed effects.

Appendix Table 1. Estimated Effects of ABLs on High School Dropout, Reprinted from Rees et al. (2022)

	(1)	(2)
	Female	Male
ABL	-0.001	0.002
	(0.005)	(0.003)
	[0.050]	[0.056]
N	52,962	55,563

[a]Significant at 1% level, [b]5% level

Notes: Weighted OLS estimates based on Current Population Survey (CPS) Basic Monthly Data are reported.

Appendix Table 2. Coefficient Estimates on Control Variables using Two-Way Fixed Effects Model, 1997-2019

	(1)	(2)	(3)	(4)	(5)	(6)
	Binge Drinking	**Tobacco Cigarette**	**Marijuana**	**Risky Sex**	**Body Mass Index**	**Overweight or Obese**
Age 15	0.032[a]	0.031[a]	0.035[a]	0.023[a]	0.383[a]	-0.028[a]
	(0.005)	(0.003)	(0.004)	(0.003)	(0.047)	(0.004)
Age 16	0.065[a]	0.076[a]	0.081[a]	0.068[a]	0.795[a]	-0.044[a]
	(0.006)	(0.006)	(0.005)	(0.005)	(0.086)	(0.007)
Age 17	0.095[a]	0.118[a]	0.112[a]	0.117[a]	10.259[a]	-0.047[a]
	(0.005)	(0.007)	(0.007)	(0.005)	(0.097)	(0.008)
Age 18	0.11[a]	0.158[a]	0.119[a]	0.157[a]	10.715[a]	-0.054[a]
	(0.006)	(0.011)	(0.008)	(0.006)	(0.119)	(0.008)
Grade 9	0.02[a]	-0.003	0.006	0.007[c]	0.167[a]	0.012[a]
	(0.006)	(0.005)	(0.005)	(0.004)	(0.042)	(0.003)
Grade 10	0.036[a]	-0.02[a]	0.005	0.02[a]	0.205[a]	0.012[b]
	(0.006)	(0.007)	(0.006)	(0.004)	(0.07)	(0.005)
Grade 11	0.07[a]	-0.024[a]	0.01	0.042[a]	0.138	0.009
	(0.007)	(0.009)	(0.008)	(0.005)	(0.084)	(0.006)
Grade 12	0.359[a]	0.382[a]	0.369[a]	0.281[a]	-0.904[b]	0.035
	(0.054)	(0.063)	(0.054)	(0.06)	(0.432)	(0.039)
White	0.085[a]	0.036[a]	0.026	-0.0003	-0.138	-0.02[a]
	(0.014)	(0.008)	(0.018)	(0.005)	(0.102)	(0.007)
Black	-0.061[a]	-0.079[a]	0.043[b]	0.028[a]	10.143[a]	0.072[a]
	(0.013)	(0.009)	(0.017)	(0.007)	(0.107)	(0.007)
Hispanic	0.058[a]	0.007	0.04[b]	0.04[a]	10.044[a]	0.081[a]
	(0.016)	(0.008)	(0.015)	(0.006)	(0.16)	(0.013)
Male	0.029[a]	0.02[a]	0.045[a]	-0.038[a]	0.595[a]	0.067[a]
	(0.002)	(0.006)	(0.003)	(0.004)	(0.039)	(0.003)
Unemployment Rate	0.349	0.175	0.466[c]	0.074	-40.996[c]	-0.388
	(0.215)	(0.281)	(0.267)	(0.131)	(20.739)	(0.246)
Per Capita Income	0.031[b]	0.018	0.014	0.008	-0.18	-0.021[c]
	(0.014)	(0.012)	(0.01)	(0.009)	(0.128)	(0.012)

Bachelor's Degree	-0.255	-0.538[a]	-0.215[c]	-0.346[a]	-40.506[a]	-0.321[b]
	(0.243)	(0.193)	(0.118)	(0.111)	(10.408)	(0.136)
Student-Teacher Ratio	-0.001	0.003	0.003	0.001	0.025	0.002
	(0.002)	(0.003)	(0.003)	(0.001)	(0.045)	(0.005)
Teacher Salary	-0.019[c]	-0.008	-0.008	-0.01[c]	0.101	0.009
	(0.009)	(0.011)	(0.007)	(0.005)	(0.091)	(0.008)
Cigarette Tax	0.003	0.006	0.013[a]	0.001	-0.017	-0.003
	(0.005)	(0.006)	(0.005)	(0.003)	(0.047)	(0.004)
E-cigarette tax	-0.017	-0.013	-0.005	0.0003	-0.045	0.002
	(0.011)	(0.009)	(0.009)	(0.005)	(0.074)	(0.01)
Beer Tax	0.006	0.007	0.012	-0.01[b]	0.007	0.001
	(0.01)	(0.012)	(0.014)	(0.005)	(0.069)	(0.005)
Sex Ed Requirement	-0.003	0.016[b]	-0.004	-0.001	-0.183[b]	-0.014[b]
	(0.01)	(0.007)	(0.006)	(0.007)	(0.071)	(0.006)
PE Credit Requirement	0.006	-0.005	-0.029[a]	-0.0002	0.0003	-0.006
	(0.013)	(0.01)	(0.009)	(0.01)	(0.114)	(0.009)
Recreational MJ Law	-0.016	-0.001	0.004	0.003	-0.011	-0.001
	(0.01)	(0.008)	(0.008)	(0.007)	(0.12)	(0.011)
Medical MJ Law	-0.006	0.001	-0.005	-0.003	-0.095	-0.006
	(0.006)	(0.005)	(0.005)	(0.005)	(0.064)	(0.005)
Observations	1,402,124	1,471,042	1,497,685	1,289,816	1,360,976	1,360,976

[a]Significant at 1% level, [b]5% level, [c]10% level

Notes: Estimated marginal effects are obtained using weighted OLS regression with data from the Youth Risk Behavior Surveys. Standard errors corrected for clustering on the state are in parentheses. All outcomes include state and year fixed effects. All regressions include survey YRBS fixed effects.

Appendix Table 3. Association between Bullying Victimization and Risky Behaviors, 2009-2019

	(1)	(2)	(3)	(4)	(5)	(6)
	Binge Drinking	**Tobacco Cigarette**	**Marijuana**	**Risky Sex**	**Body Mass Index**	**Overweight or Obese**
Bullying Victimization	0.039[a]	0.053[a]	0.046[a]	0.055[a]	0.511[a]	0.042[a]
	(0.004)	(0.005)	(0.004)	(0.003)	(0.069)	(0.006)
Weighted Mean						
N	841,463	903,841	907,344	771,486	864,453	864,453

[a]Significant at 1% level, [b]5% level , [c]10% level

Notes: Estimated marginal effects are obtained using weighted OLS regression with data from the Youth Risk Behavior Surveys. Standard errors corrected for clustering on the state are in parentheses. All regressions include controls for gender, age, grade, race/ethnicity, state unemployment rate, per capita income, and share of population with bachelor's degree.

Appendix Table 4. Estimates of Relationship Between Anti-Bullying Laws and Risky Health Behaviors, Sample Restricted to 2009-2019

	(1)	(2)	(3)	(4)	(5)	(6)
	Binge Drinking	**Tobacco Cigarette**	**Marijuana**	**Risky Sex**	**Body Mass Index**	**Overweight or Obese**
ABL	-0.011[b]	-0.0002	0.002	-0.007	-0.045	-0.0005
	(0.005)	(0.006)	(0.005)	(0.005)	(0.061)	(0.005)
Pre-Treat DepVar Mean	0.272	0.251	0.218	0.174	23.18	0.273
N	922,020	1,007,675	1,011,584	867,270	962,845	962,845

[a]Significant at 1% level, [b]5% level, [c]10% level

Notes: Estimated marginal effects are obtained using weighted OLS regression with data from the Youth Risk Behavior Surveys. Standard errors corrected for clustering on the state are in parentheses. All regressions include state and year fixed effects and controls for gender, age, grade, race/ethnicity, state unemployment rate, log per capita income, share of population with bachelor's degree, log average teacher salary, average pupil/teacher ratio, anti-cyber bullying laws, physical education credit requirements, sex education mandates, cigarette taxes, beer taxes, medical marijuana laws, and recreational marijuana laws. All regressions include survey YRBS fixed effects.

Appendix Table 5. Sensitivity of Estimates of Relationship Between State ABLs and Risky Health Behaviors to Recoding of ABL Variable, 1997-2019

	(1)	(2)	(3)	(4)	(5)	(6)
	Binge Drinking	**Tobacco Cigarette**	**Marijuana**	**Risky Sex**	**Body Mass Index**	**Overweight or Obese**
	Panel I: Recode of ABL = 1 if in Effect for Any Part of the Year; = 0 otherwise					
ABL	-0.005	0.005	-0.005	-0.007	0.028	-0.001
	(0.005)	(0.011)	(0.006)	(0.007)	(0.071)	(0.005)
	Panel II: Recode of ABL = Share of January to June for which ABL is in Effect					
ABL	-0.008	0.004	-0.004	-0.004	0.025	0.00004
	(0.005)	(0.01)	(0.006)	(0.006)	(0.065)	(0.004)
Pre-Treat Mean DepVar	0.272	0.251	0.218	0.174	23.18	0.273
N	1,402,124	1,471,042	1,497,685	1,289,816	1,360,976	1,360,976

[a]Significant at 1% level, [b]5% level, [c]10% level

Notes: Estimated marginal effects are obtained using weighted OLS regression with data from the Youth Risk Behavior Surveys. Standard errors corrected for clustering on the state are in parentheses. All regressions include state and year fixed effects and controls for gender, age, grade, race/ethnicity, state unemployment rate, per capita income, share of population with bachelor's degree, average teacher salary, average pupil/teacher ratio, physical education credit requirements, sex education mandates, cigarette taxes, e-cigarette taxes, beer taxes, medical marijuana laws, and recreational marijuana laws. All regressions include survey YRBS fixed effects.

Appendix Table 6. Sensitivity of Estimates of Relationship Between State ABLs and Risky Health Behaviors to Controls for Individual and State Observable Characteristics, 1997-2019

	(1)	(2)	(3)	(4)	(5)	(6)
	Binge Drinking	**Tobacco Cigarette**	**Marijuana**	**Risky Sex**	**Body Mass Index**	**Overweight or Obese**
			Panel I: State and Year FE and Demographic Controls			
ABL	-0.006	0.001	-0.009	-0.007	0.003	-0.002
	(0.005)	(0.01)	(0.006)	(0.006)	(0.061)	(0.005)
			Panel II: Panel I + Economic Controls			
ABL	-0.006	0.002	-0.009	-0.007	0.011	-0.001
	(0.005)	(0.01)	(0.006)	(0.006)	(0.063)	(0.005)
			Panel III: Panel II + Education and School Health Policy Controls			
ABL	-0.007	0.007	-0.008	-0.006	0.034	-0.001
	(0.007)	(0.01)	(0.007)	(0.006)	(0.066)	(0.004)
			Panel IV: Panel III + Tobacco, Alcohol, and Marijuana Policy Controls			
ABL	-0.007	0.008	-0.004	-0.005	0.038	-0.001
	(0.006)	(0.01)	(0.006)	(0.006)	(0.076)	(0.005)
			Panel V: Panel IV + Anti-Cyberbullying Laws			
ABL	-0.010	0.006	-0.008	-0.006	0.063	0.002
	(0.006)	(0.011)	(0.006)	(0.007)	(0.08)	(0.005)
Pre-Treat Mean DepVar	0.272	0.251	0.218	0.174	23.18	0.273
N	1,402,124	1,471,042	1,497,685	1,289,816	1,360,976	1,360,976

[a]Significant at 1% level, [b]5% level, [c]10% level

Notes: Estimated marginal effects are obtained using weighted OLS regression with data from the Youth Risk Behavior Surveys. Standard errors corrected for clustering on the state are in parentheses. Demographic controls include gender, age, grade, and race/ethnicity. Economic controls include state unemployment rate, per capita income, and share of population with bachelor's degree. Education and school health policy controls include average teacher salary, and average pupil/teacher ratio, physical education credit requirements, and sex education mandates. Tobacco, alcohol, and marijuana policies include cigarette taxes, e-cigarette taxes, beer taxes, medical marijuana laws, and recreational marijuana laws. All regressions include survey YRBS fixed effects.

Appendix Table 7. Unweighted Estimates of Relationship Between Anti-Bullying Laws and Risky Health Behaviors, 1997-2019

	(1)	(2)	(3)	(4)	(5)	(6)
	Binge Drinking	**Tobacco Cigarette**	**Marijuana**	**Risky Sex**	**Body Mass Index**	**Overweight or Obese**
			Panel I: TWFE Estimates			
ABL	0.001	0.007	-0.0007	-0.001	0.093	0.007
	(0.004)	(0.005)	(0.003)	(0.003)	(0.06)	(0.004)
	Panel II: Additional Controls for State-Specific Linear Time Trends and Census Division-Specific Year Fixed Effects					
ABL	-0.004	0.005	-0.003	-0.00005	0.129[b]	0.010[b]
	(0.003)	(0.004)	(0.003)	(0.003)	(0.05)	(0.004)
Pre-Treat Mean DepVar	0.265	0.231	0.213	0.167	23.08	0.261
N	1,402,124	1,471,042	1,497,685	1,289,816	1,360,976	1,360,976

[a]Significant at 1% level, [b]5% level, [c]10% level

Notes: Estimated marginal effects are obtained using unweighted OLS regression with data from the Youth Risk Behavior Surveys. Standard errors corrected for clustering on the state are in parentheses. All regressions include state and year fixed effects and controls for gender, age, grade, race/ethnicity, state unemployment rate, log per capita income, share of population with bachelor's degree, log average teacher salary, average pupil/teacher ratio, anti-cyber bullying laws, physical education credit requirements, sex education mandates, cigarette taxes, e-cigarette taxes, beer taxes, medical marijuana laws, and recreational marijuana laws. All regressions include survey YRBS fixed effects.

Appendix Table 8. Estimates of Relationship Between Anti-Bullying Laws and Risky Behaviors on School Property, 1997-2019

	(1)	(2)	(3)
	Tobacco Use On School Property	**Alcohol Use on School Property**	**Drug Presence on School Property**
ABL	-0.004	-0.001	-0.012[c]
	(0.003)	(0.003)	(0.007)
Weighted Mean	0.087	0.049	0.272
N	624,871	659,942	1,229,701

[a]Significant at 1% level, [b]5% level, [c]10% level

Notes: Estimated marginal effects are obtained using weighted OLS regression with data from the Youth Risk Behavior Surveys. Standard errors corrected for clustering on the state are in parentheses. All regressions include state and year fixed effects and controls for gender, age, grade, race/ethnicity, state unemployment rate, per capita income, share of population with bachelor's degree, average teacher salary, average pupil/teacher ratio, physical education credit requirements, sex education mandates, cigarette taxes, beer taxes, e-cigarette taxes, medical marijuana laws, and recreational marijuana laws. All regressions include survey YRBS fixed effects.

Appendix Table 9. Estimated Effect of ABLs on the Probability that Youth Identifies as LGBQ

	(1)	(2)
ABL	0.002	0.002
	(0.009)	(0.006)
Weighted Mean	0.06	0.06
State and Year FE?	Yes	Yes
Column (3), Table 3 Controls	Yes	Yes
Tobacco Policy Controls?	No	Yes
Alcohol Policy Controls?	No	Yes
Marijuana Policy Controls?	No	Yes
School Health Policy Controls?	No	Yes
Observations	680,419	680,419

[a]Significant at 1% level, [b]5% level, [c]10% level

Notes: Estimated marginal effects are obtained using weighted OLS regression with data from the Youth Risk Behavior Surveys. Standard errors corrected for clustering on the state are in parentheses. Tobacco policy controls include the state cigarette tax and e-cigarette tax, alcohol policy controls include the state beer tax, marijuana policy controls include medical and recreational marijuana laws, and school health policy controls include sex education and physical education requirement laws. All regressions include survey YRBS fixed effects.