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ABSTRACT

Evaluating Alcohol Exclusion Provisions in Health Insurance: Evidence from the Uniform Accident and Sickness Policy Provision Laws*

Alcohol exclusion provisions, embedded in the Uniform Accident and Sickness Policy Provision Law (UPPL), allow health insurance providers to punish alcohol consumption by permitting them to deny claims for injuries stemming from alcohol impairment or the use of non-prescribed narcotics. Although the UPPLs were originally proposed to discourage excessive drinking and substance use, there is no clear evidence to either support or refute that these laws achieved their intended purpose. Furthermore, few studies document that these laws may have unintended consequences, as they create a disincentive for physicians to test the blood alcohol concentration (BAC) levels of injured patients due to concerns about potential insurance reimbursement denials. We provide a comprehensive analysis of the UPPLs by investigating their impact on alcohol consumption at the intensive and extensive margin, drunk driving behavior, alcohol-related traffic fatalities, alcohol-related crime, and health insurance coverage rates and premiums.

JEL Classification: I10, I18

Keywords: alcohol exclusion provisions, Uniform Accident and Sickness Policy Provision Law, alcohol consumption, alcohol consumption related outcomes

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1 Introduction

Excessive alcohol consumption statistics in the United States are alarming. More than half of adults in the United States report drinking alcohol in the past 30 days. Approximately 17% of adults binge drink and 6% report heavy drinking.[1] During $2015-2019$, excessive alcohol use was responsible for more than $140,000$ deaths and 3.6 million years of potential life lost each year, on average. More than 40% of these deaths and half of the years of potential life lost were due to binge drinking (Substance Abuse and Mental Health Services Administration, 2019a and 2019b). In addition to its impact on public health, the economic ramifications of excessive alcohol use are significant, with an estimated cost of $249 billion in 2010 in the United States alone (Centers for Disease Control and Prevention, 2018). Moreover, there was a 61.6% increase in emergency department visits related to alcohol consumption between 2006 and 2014, resulting in a 272% surge in total costs, escalating from $4.1 billion to $15.3 billion (White, et al., 2018).

With a primary intent of reducing excessive alcohol consumption, the alcohol exclusion provisions, embedded in the Uniform Accident and Sickness Policy Provision Law (UPPL), allow health insurance providers to explicitly punish alcohol consumption by permitting them to deny claims for injuries stemming from alcohol impairment or the use of non-prescribed narcotics. First adopted in a few states in 1951, the peak number of states with UPPLs was in 1998, when 40 states had such laws. Although the primary intention behind UPPLs was to discourage excessive drinking and substance use, the evidence that shows that the UPPLs achieved their intended purpose is non-existent, and some studies suggest that these laws may have unintended consequences, as they create a disincentive for physicians to test the blood alcohol concentration (BAC) levels of injured patients due to concerns about potential insurance reimbursement denials (Rivera, et al., 2000 and Schermer, et al., 2003) and decrease the number of admissions for alcohol treatment from healthcare professional referrals (Azagba, et al., 2022b). This is particularly important since the Substance Abuse and Mental Health Services Administration (SAMHSA) recommends that primary care clinicians periodically and routinely screen all patients for substance use disorders (SAMHSA, 1997). Based on the existing evidence and recognizing that alcohol dependency is a chronic illness responsive to treatment, major stakeholders such as the National Association of Insurance Commissioners (NAIC) and American Public Health Association (APHA) recommended the repeal of the UPPLs in 2001 and 2004, respectively (National Conference of Insurance Legislators, 2004 and American Public Health Association, 2004).

[1] Most recent estimates from the Behavioral Risk Factor Surveillance System of the Centers for Disease Control and Prevention. Available at: https://www.cdc.gov/alcohol/data-stats_1.htm (Accessed on January 24, 2024).

Since then, several states repealed their UPPLs. However, as of 2022, there are still 23 states with these laws.

The effects of the UPPLs on alcohol consumption and alcohol consumption outcomes are ambiguous. On the one hand, repeal of the UPPLs and explicitly prohibiting the denial of health insurance claims due to intoxication may encourage excessive drinking and increase alcohol-related problems as they eliminate the punishment in health insurance policies associated with alcohol consumption. Health insurance coverage may reduce an individual's incentive to take preventive efforts to remain healthy (Chen, et al., 2023). It is possible that repeal of these laws increases an individual's propensity to engage in risky behaviors including excessive alcohol consumption. On the other hand, there are four main reasons why UPPLs may not have their intended impact. First, if these laws disincentivize the testing of the BAC and more comprehensive probing of patients' involvement with alcohol, patients who expect that they will not be tested for the BAC may be unlikely to alter their drinking behavior. Second, physicians and patients may not be fully aware of the existence of the UPPLs. For example, Gentilello, et al. (2005) argue that trauma center surgeons' familiarity with the UPPL was limited while Subbaraman, et al. (2022) argue that many Americans do not know their alcohol treatment coverage and that the prevalence of this uncertainty has increased over time. Third, even in states with UPPLs, competition among insurance providers may lead to more generous health insurance coverage policies without any alcohol exclusion provisions since the existence of the UPPLs gives an option but does not force providers to include alcohol exclusion provisions in health insurance policies. Fourth, since UPPLs are part of private health insurance policies, their impact on those who have public coverage is expected to be limited.[2] Therefore, estimating the impact of the UPPLs on alcohol consumption and related outcomes is important and can provide useful insights to the states considering repealing these laws.

The existing literature on the effectiveness of UPPLs is very limited and most of it is descriptive. Among the few studies that provide an empirical analysis of the effects of the UPPLs, Azagba, et al. (2022a) find no statistically significant impact of these laws only on the binary indicators of alcohol consumption and binge drinking. Azagba, et al. (2022b) investigate the effects of these laws on alcohol treatment utilization and document that alcohol treatment admissions by healthcare professional referrals for patients covered by private insurance increased by about 38% in states that repealed their UPPLs compared to states that did not repeal these laws. Both of these studies

[2] According to the recent estimates from the U.S. Census Bureau (2023), Utah and North Dakota had the highest (78.4%) and New Mexico the lowest (54.4%) rates of private coverage in 2022, compared with the national average of 67.2%.

focus on the repeal of UPPLs. However, the repeal of the UPPL does not guarantee that insurance companies cannot deny claims resulting from alcohol impairment unless the repeal of the UPPL simultaneously occurred with the introduction of another law that specifically prohibited the denial of claims due to intoxication. In fact, most states that repealed their UPPLs simultaneously replaced them with laws that prohibited denial of insurance claims due to intoxication. However, some states either did not have a UPPL law to begin with, or did not introduce any law that prohibits denial of insurance claims due to alcohol involvement following the repeal of the UPPL. In these states, the response of insurance providers is not clear. Without the existence of any law that explicitly prohibits denials, courts have ruled that insurance companies can still deny claims due to alcohol involvement (Teitelbaum, Rosenbaum, and Goplerud, 2004). A more accurate assessment of the effectiveness of the UPPLs should rely on a separate comparison of the outcomes of the states with a UPPL with those where denial of health insurance claims is prohibited and those where no UPPL-related law exists. Azagba, et al. (2022a and 2022b) also rely on traditional two-way fixed effects (TWFE) models. Recent findings in the difference-in-difference (DID) literature show that when the adoption of a treatment is staggered and average treatment effects vary across groups and over time, TWFE models may not identify an easily interpretable measure of the typical effect of the treatment (de Chaisemartin and D'Haultfœuille, 2020; Sun and Abraham, 2020, and Gardner, 2021). To overcome this potential problem, we rely on two-stage difference-in-differences (TSDID) models that are robust to treatment-effect heterogeneity when the adoption of the treatment is staggered (Gardner, 2021).

Our paper makes several other contributions to the existing literature by estimating the effects of the UPPLs on several alcohol consumption and alcohol consumption-related outcomes for the first time. These outcomes include alternative indicators of alcohol consumption for the intensive margin such as the number of days of drinking and binge drinking per month and average number of drinks per day, and different indicators of drunk driving, alcohol-related crime, health insurance coverage status, and health insurance premiums. Our paper is also the first to estimate models for different subsamples including models estimated separately by gender and for different age groups.

Our main results are based on data from the $1998-2021$ Behavioral Risk Factor Risk Surveillance System (BRFSS). We restrict our sample to those who have health insurance and are younger than 65 because almost all Americans are covered by a public insurance plan (Medicare) after this age. We find that although the states that explicitly prohibited alcohol exclusion provisions in the UPPLs experienced an increase in binge drinking, this effect is not statistically significant. For those who consume alcohol at least once a month and reside in a state that prohibited alcohol exclusion provisions in the UPPLs, we find a statistically significant but relatively small (0.07 times a month) increase in number of times that the respondent drove in the past month after drinking too much. Our results indicate that UPPLs do not have a significant impact on traffic fatalities resulting from alcohol or drug use or alcohol-related crimes. Similarly, we document that our findings cannot be attributed to the potential differences in health insurance providers' pricing behavior in the presence or absence of the UPPLs since these laws do not have a significant impact on health insurance premiums or coverage rates. These results show that alcohol exclusion provisions, embedded in UPPLs, often do not achieve their intended purpose of reducing excessive alcohol consumption and are not effective in reducing alcohol-related traffic fatalities or crimes.

2 Background and literature review

Laws permitting the use of intoxication exclusionary clauses in insurance contracts have their roots in the 1947 UPPL, a non-binding model statute drafted by NAIC (Teitelbaum, Rosenbaum, Goplerud, 2004). In 1951, Kansas and Pennsylvania became the first two states to adopt a UPPL (Azagba, Ebling, and Hall, 2023). By the mid-1950s, most states had adopted the UPPL in principle. The content of the UPPL is relatively similar across different states that have these laws. Cochran (2010) argues that among those states with a UPPL, there are no meaningful differences between each state's law.

The Alcohol Policy Information System (APIS) of the National Institute on Alcohol Abuse and Alcoholism provides the exact date of policy changes related to UPPLs for each state since 1998. We provide a summary of this information in Appendix Table A1. From 1998 to 2021, insurance providers are permitted to deny claims for injuries resulting from alcohol impairment or the use of non-prescribed narcotics in 22 states. During this period, only in one state (South Dakota), insurance companies were explicitly prohibited from denying claims due to intoxication, while in 8 states, there was no specific UPPL-related policy. Our identification in empirical models comes from 20 states, where there was a UPPL-related policy change between 1998 and 2021. For the majority of these policy changes, states that repealed their law that permitted the denial of health insurance claims due to intoxication replaced it with another law that explicitly prohibited the denial of health insurance claims due to intoxication. However, this was not always the case and some states that repealed their UPPLs did not replace them with another UPPL-related law. We incorporated this possibility in our empirical models by estimating the separate effects of prohibiting the denial of claims due to intoxication and having no UPPL-related policy on outcome variables.

Appendix Figure A1 shows the distribution of the states across the United States based on the UPPL status as of 2022. While the states that allow denial of benefits due to intoxication are mostly located in the East, the geographical distribution of the states that either have no UPPL or prohibit the denial of benefits due to intoxication appears to be random.

In three states, the scope of UPPLs is not clear as the relevant law allows some exceptions. In Maine, from September 20, 2007, until now, intoxication exclusions are prohibited in health insurance contracts with the exception that they are permitted in group or blanket policies. In Maryland, between October 30, 2000, and December 31, 2001, intoxication exclusions were permitted by statute in individual health insurance policies but were prohibited by regulation in group health insurance policies, individual and group health maintenance contracts, and individual nonprofit health service plans. In New Jersey, from May 6, 2019 until now, a blanket insurance policy or certificate or other group policy or certificate providing health insurance may include an exclusion for losses resulting from the covered person's use of alcohol, but this does not apply to a group health benefits plan. Previous studies did not attempt to address this potential problem and it is not clear how the treatment status for these states was determined in these studies (Azagba, et al. 2022a; Azagba, et al. 2022b). Since most private health insurance policies are group policies, in our main models, we assume that Maine has a UPPL while Maryland and New Jersey explicitly prohibit the denial of claims due to intoxication for the relevant periods. However, as a robustness check, we also estimate alternative models for which we exclude the data for these states for the relevant periods from our sample.

From a general perspective, the UPPLs provide a natural experiment to test the moral hazard problem in health insurance, which has been difficult to test empirically (Einav and Finkelstein, 2018). The classical economic theory suggests that because health insurance covers the financial costs that would be caused by risky health behaviors, individuals may have less incentive to avoid them if they have insurance coverage (Ehrlich and Becker, 1972). In the context of the UPPLs, it is plausible that prohibiting alcohol exclusion provisions in health insurance policies may lead to more alcohol consumption and an increase in alcohol-related risky behaviors as they reduce the financial costs of health care associated with these behaviors for the insured. This effect may be more pronounced for populations with high alcohol consumption rates. Yet, the literature on the effects of the UPPLs is very limited and most of the existing studies are descriptive. Teitelbaum, Rosenbaum, Goplerud (2004) and Azagba, Ebling, and Hall (2023) provide a brief history of the UPPLs and discuss relevant policy implications without providing an empirical analysis of the potential effects of these laws. Chezem (2004) categorizes UPPLs as one of the legal barriers to alcohol screening in emergency departments and trauma centers. Gentilello, et al. (2005) argue that trauma center surgeons' familiarity with the UPPL was limited. But, despite the lack of knowledge of the UPPL, 24% reported an alcohol- or drug-related insurance denial in the past 6 months. They argue that this affects screening practices as the majority of surgeons do not routinely measure the BAC. Among the few empirical studies, O'Keefe, et al. (2009) focus primarily on the effects of alcohol intoxication on increased use of diagnostic and therapeutic procedures in trauma centers. They argue that since alcohol intoxication increases resource utilization, health insurance denials due to the UPPLs compound the financial burden of alcohol use on trauma centers. They suggest that the UPPLs that penalize trauma centers for identifying intoxicated patients should be repealed. Azagba, et al. (2022b) and Azagba, et al. (2024) investigate the effect of the repeal of the UPPLs on alcohol-related treatment admissions. Azagba, et al. (2022b) show that the number of admissions for alcohol treatment from healthcare professional referrals increased by 16% in the UPPL repeal states compared to states with UPPLs or that never had UPPLs. Similarly, Azagba, et al. (2024) find that the repeal of the UPPLs in Colorado and Illinois was associated with higher treatment admissions from 2008 to 2011. Azagba, et al. (2022a) investigate the effects of the repeal of the UPPLs on alcohol consumption for the extensive margin, i.e., whether the respondent reported drinking or binge drinking at least once in the past 30 days. They find that repealing UPPLs has no statistically significant impact on these outcomes.

Our paper makes several important contributions to the literature on the effects of the UPPLs on alcohol consumption and related outcomes. First, categorizing states without a UPPL in the same category as control states (states with UPPLs) as in Azagba, et al. (2022a, 2022b, and 2024) may not be appropriate. Our paper is the first to recognize this potential problem and explicitly model the fact that when states repeal their UPPLs, they do not always introduce a new law that explicitly prohibits the denial of benefits due to intoxication. Second, recent advancements in the DID literature demonstrate that when the adoption of treatment is staggered and average treatment effects vary across groups and over time, traditional TWFE models may not identify an easily interpretable measure of the typical effect of the treatment (de Chaisemartin and D'Haultfœuille, 2020; Sun and Abraham, 2020, and Gardner, 2021). Therefore, results based on TWFE models (Azagba et al., 2022a and 2022b) are likely to be biased. We address this problem by estimating TSDID models (Gardner, 2021) that are robust to treatment-effect heterogeneity when the adoption of the treatment is staggered. Third, in addition to estimating the effects of the UPPLs on alcohol consumption for the extensive margin (Azagba et al., 2022a), we also estimate the impact of the UPPLs on alcohol consumption for the intensive margin, i.e., the number of days of drinking and binge drinking per month and average number of drinks per drinking episode. Fourth, our paper is the first the estimate the effect of the UPPLs on various outcomes including different indicators of drunk driving, alcohol-related crime, health insurance coverage status, and health insurance premiums. Finally, our paper is the first to estimate models for different subsamples including models estimated separately by gender and for different age groups.

3 Data

We use several data sets to estimate the effect of the UPPLs on various alcohol consumption, drunk driving, alcohol-related crime, and health insurance coverage and cost outcomes. For each data set, we provide the description of our outcome variables and summary statistics in Appendix Table A2. Our main data come from the $1998-2021$ waves of the BRFSS, which is a nationally representative health survey conducted annually by the Centers for Disease Control and Prevention (CDC). BRFSS interviews more than $400,000$ noninstitutionalized adults (18 and older) by phone each year, making it the largest continuously conducted health survey system in the world. A major advantage of the BRFSS is that due to its sample size, it is suitable for subsample analysis. The UPPLs are part of the private insurance policies and can only affect those who are insured. Therefore, for the majority of our analysis, we restrict our sample to those who have health insurance and are under 65 since almost all the U.S. population who are 65 and older are covered under Medicare, which does not include any UPPL-related provisions.

In addition to standard demographic information, the BRFSS respondents were also asked detailed questions about their alcohol consumption habits. To investigate the effects of the repeal of the UPPLs on alcohol consumption both at the intensive and extensive margin, following Yörük (2014), we consider five alternative indicators of alcohol consumption. Two of these indicators are binary measures of drinking participation, i.e., whether the respondent consumed alcohol over the past month at least once and whether the respondent engaged in heavy (binge) drinking in the past month at least once.[3] Two of the remaining indicators are measures of drinking episodes per month, i.e., the number of days that the respondent had at least one drink and the number of days that she had five or more drinks on the same occasion. The remaining indicator of alcohol consumption measures the intensity of drinking as the average number of drinks that the respondent consumed per day during

[3] These variables are not observed directly. We derive them using information on the number of days that respondents reported drinking alcohol in the past month.

the past month.

The BRFSS also includes questions related to health insurance coverage and driving under the influence of alcohol. Driving under the influence of alcohol questions were asked biennially and only to those who reported consuming alcohol at least once in a given month. We use these questions to estimate the effect of the repeal of the UPPLs on the probability of having health insurance, the probability of driving after drinking too much, and the number of times that the respondent reported driving in a given month after drinking too much.

Since 2011, the CDC started making survey calls to cell phone numbers in addition to landlines to keep the data representative of the U.S. population. Furthermore, it changed the statistical method used to compute sampling weights, moving from post-stratification to iterative proportional fitting (Pierannunzi et al., 2012). We follow prior research that pools all BRFSS waves and adjusts weights accordingly (Simon et al., 2017). But, given these methodological changes, we also test the robustness of our results by estimating models that use data only for the pre-2011 period.

We supplement BRFSS data on driving under the influence of alcohol with data from the Fatality Analysis Reporting System (FARS), which contains information on all vehicle traffic crashes that include a fatal inquiry. FARS reports data in several modules. We use person-level data from 1998 to 2021 and aggregate it to month-year level for each state.[4] Our main focus is the crashes in which the driver is identified by the police as operating under the influence of alcohol or drugs. For this analysis, we consider two outcomes. The first is the share of under-the-influence drivers at a given month in the full sample of drivers in the FARS person-level data. Appendix Table A2 shows that approximately 19% of all drivers who were involved in a fatal crash were under the influence of alcohol or drugs. The second is the number of under-the-influence drivers that involved in a fatal crash per $100,000$ people per calendar month for each state.

To investigate the impact of the repeal of the UPPLs on alcohol-related crimes, we use data from the 1998−2021 waves of the National Incident-Based Reporting System (NIBRS). The NIBRS contains detailed information on each crime incident reported by police agencies (departments) registered in this system. For each state, we aggregate these data to the month-year level. Since participation in the NIBRS is voluntary and police departments may not report crime data at all or for certain crime categories and periods, the sample size from the NIBRS is relatively small, and measuring crime levels per capita for each state may not be reliable. To overcome this potential problem, we focus on shares of alcohol-related crimes among other crimes that are classified similarly. The NIBRS

[4] We drop 38 state-month-year observations because there were no fatal crashes during those time periods.

classifies crimes into two major categories. Group A offenses are serious violent and property crimes such as assault, vandalism, robbery, and burglary. Group B offenses are minor crimes that include alcohol-consumption-related crimes among others. For our analysis, we consider three outcomes from the NIBRS group B offenses. These are shares of driving-under-the-influence (DUI) arrests, public drunkenness arrests, and liquor law violation arrests among the total category B crimes in a given calendar month in a particular state.

Although the BRFSS provides information on health insurance coverage, it is not possible to determine the type of coverage for those who are covered. To address this potential problem, we supplement BRFSS with data from the Medical Expenditure Panel Survey (MEPS). The Insurance/Employer Component (MEPS-IC) provides aggregated data on the private health insurance plans offered, benefits, annual premiums, and annual contributions for each year and state. We used data from the 1998 − 2021 MEPS-IC to estimate the effects of the repeal of the UPPLs on several outcomes including the percentage of private sector employees enrolled in a health insurance plan that takes single coverage, average total single premium per enrolled employee at private-sector establishments that offer health insurance, and annual percentage change in average total single premium per enrolled employee at these establishments.[5]

4 Methodology

Our estimation strategy relies on the variation in the staggered adoption of the UPPLs over time and across states. We also incorporate recent advancements in difference-in-differences literature into our empirical analysis. Recent literature has shown that when the adoption of treatment is staggered and average treatment effects vary across groups and over time, the traditional TWFE model may not identify an easily interpretable measure of the typical effect of the treatment (Athey and Imbens, 2018; Goodman-Bacon, 2018; de Chaisemartin and D'Haultfœuille, 2020; Imai and Kim, 2020; Sun and Abraham, 2020, and Gardner, 2021).[6] To explicitly address this potential problem, we use a two-stage difference-in-differences (TSDID) model developed in Gardner (2021) that is robust to treatment-effect heterogeneity when the adoption of treatment is staggered and present the results

[5] The MEPS-IC does not report data for 2007.

[6] Gardner (2021) argues that the TWFE identifies the average of potential heterogenous treatment effects if those those effects are distributed identically across treatment groups and time periods. However, when identical distribution assumption fails to hold, conditional mean outcomes are not linear in group, time, and treatment status, which leads to the misspecification of the traditional TWFE model. In this case, the TWFE cannot identify the average effect of the treatment on the treated.

from this model alongside the estimates from the TWFE model for comparison. The traditional TWFE model in our setting can be expressed as:

$$Y_{ismt} = \beta' \mathbf{X}_{ismt} + \alpha' \mathbf{S}_{smt} + \lambda_1 prohibit_{ismt} + \lambda_2 nolaw_{ismt} + \mu_s + \gamma_{mt} + e_{ismt}, \tag{1}$$

where i indexes individuals, s indexes states, m indexes months, and t indexes years. In this model, Y_{ismt} represents the variety of alcohol consumption, drunk driving, alcohol-related crime, and health insurance coverage and cost outcomes. Set of individual and state-level controls are denoted by $\mathbf{X}_{ismt}$ and $\mathbf{S}_{smt}$, respectively. Individual-level control variables include household income, the number of children in the household who are younger than 18, and dummy variables controlling for race, gender, age, educational attainment, and employment, marital, and health insurance coverage status.[7] State-level control variables include median income, unemployment rate, and shares of females, those who belong to different racial groups, those who have different educational attainment levels, and those who are covered by a health insurance plan in the population.[8] $\mathbf{S}_{smt}$ also includes a full set of variables that control for the presence of other alcohol and substance abuse regulations at the state level. These policies are BAC limits, restrictions on the sale of alcohol on Sundays, beer taxes, and medical marijuana laws.[9] In equation (1), μ_s and γ_{mt} represent state fixed effects and month-year (calendar month) fixed effects that control for potential seasonality in alcohol consumption. The majority of results that we present are from models that do not include state-specific linear time trends that control for a variety of other variables that may be associated with the outcomes, but trend smoothly within states over time. This is because the inclusion of state-specific linear time trends may reduce identifying variation and obscure treatment effects if there are dynamic effects of the repeal of the UPPLs (Wolfers, 2006 and Neumark et al., 2014). However, we also present the results from models that include state-specific linear time trends in the Appendix. In general, our results are robust under this alternative specification.

In equation (1), the treatment variables of interest are $prohibit_{ismt}$ and $nolaw_{ismt}$. These binary variables are equal to one for those who reside in one of the states that either explicitly prohibits the denial of health insurance claims due to intoxication ($prohibit_{ismt}$) or has no effective UPPL-related

[7] The BRFSS reports annual household income in different income categories. For each category, we used the mid-point as a proxy for income, adjust it with inflation to reflect 2021 prices, and use the natural logarithm of this variable as an independent variable.

[8] We use the natural logarithm of state-level median income adjusted for inflation to reflect 2021 prices. Shares of different racial groups include whites, blacks, and Hispanics. Shares of those with different educational attainment levels include high school, some college, and college graduates.

[9] The sources for these policies include the APIS, tax foundation, and ProCon.org.

law ($nolaw_{ismt}$) at month m of year t.[10] Given that the UPPLs operate only for private insurance, and not all private insurers deny coverage as a result of intoxication even in states with UPPLs, the coefficients on these treatment variables (λ_1 and λ_2) provide the intention-to-treat impact of the policy on outcome variables compared to the states that explicitly permit the denial of health insurance claims due to intoxication. Models with binary dependent variables are estimated as linear probability models for ease of interpretation and in all regressions, standard errors are corrected for clustering at the state level (Bertrand et al., 2004). Models estimated using samples from the BRFSS also include sample weights.

Following Gardner (2021) and Gardner, et al. (2023), we estimate the TSDID model in two steps. In the first stage, we regress each outcome variable on a full set of controls, and state and time fixed effects using the subsample of untreated observations. In the second state, we subtract the estimated effects from this model from the outcome variable and regress the resulting residualized outcome on treatment variables.[11] Under the assumption that outcome variables in treatment and control states exhibit similar trends before the policy change, this model identifies the overall average effect of the treatment on the treated, even when average treatment effects are heterogeneous over groups and periods. In this model, our first stage regression is:

$$Y_{ismt} = \beta_1' \mathbf{X}_{ismt} + \alpha_1' \mathbf{S}_{smt} + \mu_s + \gamma_{mt} + v_{ismt}, \tag{2}$$

which we estimate for control states (states that explicitly permit the denial of health insurance claims due to intoxication at a given time) for which $prohibit_{ismt} = 0$ or $nolaw_{ismt} = 0$, or alternatively $permit_{ismt} = 1$. Next, we calculate the residuals from this model and regress them on treatment variables. Therefore, our second stage models is:

$$Y_{ismt} - \widehat{Y_{ismt}} = \delta_1 prohibit_{ismt} + \delta_2 nolaw_{ismt} + u_{ismt}. \tag{3}$$

The key identification assumption in both the TWFE and TSDID models is that, in the absence of the UPPLs, outcome variables would have trended similarly between treatment and control states. One potential threat to this identification strategy is that the decision to permit the denial of health insurance claims due to intoxication may reflect policy endogeneity. In particular, states that experienced relatively higher alcohol consumption rates might be more likely to permit the denial of

[10] Except for the MEPS-IC sample, we assumed that the month of the policy change is in the treatment group if the policy change occurred before the 15th of that particular month. For the MEPS-IC sample that contain state-year level information, we assumed that the year of the policy change is in the treatment group if the policy change occurred within the first six months of that particular year.

[11] We use the Stata routine "did2s" to estimate this model.

health insurance claims due to intoxication compared with those states with relatively lower alcohol consumption rates. Figure 1 shows that states that repealed the UPPLs could not have done it as a reaction to decreasing alcohol consumption over time. As illustrated in this figure, trends in alcohol consumption and binge drinking are fairly similar across states that repealed the UPPLs and those that did not prior to the repeal of these laws.[12] Furthermore, to address concerns of policy endogeneity formally, we extend the TWFE and TSDID models to estimate the dynamic effects of the policy changes. In this model, we replace the treatment variable for states that prohibited the denial of insurance claims due to intoxication with a series of dummy variables that cover 6-month periods before and after the policy change and use the six months just before the policy change as the reference group. Our estimates of the effect of the repeal of UPPLs on different outcomes have causal interpretation if states with and without the UPPLs have similar trends before the repeal of the UPPLs, that is, if coefficients of the policy lead coefficients are not significantly different from zero.

5 Results

5.1 Alcohol consumption

Table 1 reports the effect of the repeal of the UPPLs on several different indicators of alcohol consumption. For the extensive margin, our results show that prohibiting alcohol exclusion provisions in health insurance policies is associated with up to a 2.5 percentage point increase in the probability of consuming alcohol and up to a 0.5 percentage point increase in the probability of engaging in binge drinking in the past month. However, these effects are not statistically significant. The precision of the null effects allows us to rule out, with 95% confidence, policy-induced increases in the probability of engaging in binge drinking in the past month of more than 12.2 percent compared with the mean of this variable.

Similarly, for the intensive margin, we find that prohibiting alcohol exclusion provisions increases

[12] Since UPPLs repealed at different times at different states, Figures 1 is centered in the exact date the policy has changed in the states that repealed the UPPLs and started explicitly prohibiting the denial of health insurance claims due to intoxication (time 0) and plot alcohol consumption trends in the months leading up to and after this period for 60 months in 1-month blocks. For the control and "no law" states, average alcohol consumption trends during the same period are plotted. For instance, suppose that there are two "prohibit" states (state A and B) and one control state ("permit") during the analysis period (state C). Suppose further that the repeal of the UPPL became effective on 3/5/2005 in state A and on 12/11/2003 in state B. The average alcohol consumption at time 0 in state C is based on alcohol consumption rates in state C on 3/5/2005 and 12/11/2003.

drinking episodes as well as the average number of drinks consumed per day. However, these estimates are not statistically significant and their magnitude is small. The estimated effects of the repeal of the UPPLs on the number of days that the respondent engaged in binge drinking is negative and statistically insignificant. The precision of the estimate in a TSDID model that includes full set of control variables (-0.035 with a standard error of 0.030) allows us to rule out, with 95% confidence, policy-induced increases in this outcome of more than 3.2 percent compared with the mean of this variable.

As a robustness check, estimating similar models for the entire BRFSS sample that includes those who do not have health insurance coverage and those who are older than 65 generates similar and statistically insignificant results as expected (Appendix Table A3). The only exception for this sample is the relatively small (2.6 percentage points) and marginally significant increase in the probability of drinking alcohol due to prohibiting alcohol exclusion provisions. The second column in Appendix Table A3 reports results for those who do not have health insurance. Not surprisingly, for this group, the impact of the UPPLs on all alcohol consumption outcomes is statistically insignificant.

Results from the TSDID models reported in Table 1 also show that compared to the states with UPPLs, states with no UPPL-related laws experience in increase alcohol consumption. This effect is statistically significant for the probability of consuming alcohol but relatively small and not significant at conventional levels for the remaining outcomes.

In Appendix Table A4, we present results from models that include state-specific linear time trends. For the main sample, inclusion of state-specific linear time trends do not have meaningful impact on the estimated effect of the UPPLs on alcohol consumption. Results from the TWFE and TSDID models suggest that prohibiting alcohol exclusion provisions in the UPPLs increases various indicators of alcohol consumption. However, these effects are small and not statistically significant.

5.1.1 Heterogeneous effects

In Table 2, we investigate whether the UPPLs' effects on alcohol consumption differ by gender. For females, although the results from the TWFE suggest that prohibiting alcohol exclusion provisions significantly increases both the probability and episodes of engaging in binge drinking, the findings from the TSDID models do not support this finding. Compared with females, the effects of the UPPLs on males' drinking behavior are less pronounced and almost always statistically insignificant. Appendix Table A4 shows that the inclusion of the state-specific linear time trends to empirical models do not change these findings with the exception of average number of drinks consumed per day. Results from the TSDID model that include state-specific linear time trends suggest that for females, prohibiting alcohol exclusion provisions is associated with a 0.134 drink increase in the average number of drinks consumed per day. This effect is smaller but still statistically significant in the TWFE model.

We estimate similar models for different age groups and report our results in Table 3. The results reveal that the repeal of UPPLs does not have a heterogenous impact on the drinking behavior of people that belong to different age groups. Although the probability of consuming alcohol and engaging in binge drinking increases slightly for all age groups as a response to prohibiting alcohol exclusion provisions in health insurance policies, this effect is not statistically significant at conventional significance levels.

People under age 65 who live in middle or high income households are much more likely to have health insurance coverage compared to those from low-income households. Furthermore, these people are more likely to be covered by a private insurance rather than a public insurance plan (Crimmel, 2004). Therefore, it is possible that the people from high-income households are more likely to be affected from the repeal of the UPPLs. Appendix Table A5 shows that this is not the case. Prohibiting alcohol exclusion provisions in UPPLs does not have significant impact on the various indicators of alcohol consumption and the impact of the policy does not appear to differ by household income. In Appendix Table A6, we document a similar result for people with different educational attainment levels.

5.1.2 Robustness checks

Table 4 reports results from several robustness checks. As we have discussed before, for certain periods and states, the scope of UPPLs is not clear as the relevant law allows some exceptions in Maryland, Maine, and New Jersey. We find that excluding these periods for these three states does not alter our finding that the UPPLs are not significantly associated with different indicators of alcohol consumption.

The second specification tests whether dropping states with no UPPL-related laws from the sample affects the main results. The estimated coefficients on the treatment variable ($prohibit_{ismt}$) in this model are similar to those reported in Table 1 and remain statistically insignificant.

During the COVID-19 pandemic, sweeping lockdowns and other aggressive measures that control the sale and distribution of alcohol were put in place and retained in many states until late 2020. In addition, during this period, alcohol consumption in the United States increased considerably

(Grossman, Benjamin-Neelon, and Sonnenschein, 2020). These changes may confound our estimates. To address this possibility, we drop the observations for the COVID and post-COVID periods and estimate models using only data before 2020. The results from these models are similar to those from the main models and document the statistically insignificant impact of the UPPLs on alcohol consumption.

In 2011, the CDC started making survey calls to cell phone numbers in addition to landlines to keep the data representative of the U.S. population. It also changed the statistical method used to compute sampling weights, moving from post-stratification to iterative proportional fitting (Pierannunzi et al., 2012). To address this problem, we estimate models using data only before 2011. Although this means that we do not use 10 years of data for $2012 - 2021$, our estimation strategy is still valid since the majority of policy changes related to the UPPLs occurred before 2011. The results from this alternative specification are also similar to our main findings and confirm that the UPPLs did not achieve their intended purpose of reducing excessive alcohol consumption for the main sample of those who are younger than 65 and have health insurance coverage.

In Table 5, we provide results from an alternative stacked DID approach that is used to estimate causal impacts in staggered policy designs. This approach uses only control states that are untreated as counterfactuals for the treated states (Cengiz et al., 2019). To estimate this model, we first drop states that have either no effective alcohol exclusion provisions (no law states) in the UPPLs in any period during $1998 - 2021$ or always prohibited these laws (South Dakota) from our sample. Next, for each UPPL-related policy change event (transition from permit to prohibit state), we consider a nine-year window, inclusive of the effective year, four years before, and four years after the event, and construct our control group from those states where the policy has not yet been implemented and did not change during this nine-year window. We use each UPPL-related policy change event and control states to make a stack and append the stacks to construct our final estimation sample. We estimate a model similar to equation (1) but also control for fixed stack effects. The results reported in Table 5 support our findings from the TSDID models and show that removing alcohol exclusion provisions in the UPPLs does not have a significant impact on various indicators of alcohol consumption for the main sample of those who are under 65 and have health insurance.

5.1.3 Dynamic effects

In Figures 2 to 4, we report the dynamic impact of the UPPLs on different indicators of alcohol consumption for the main sample and subsamples based on gender. For the main sample, the results reported in Figure 2 show that the long-run effects of removing alcohol exclusion provisions in the UPPLs on different indicators of alcohol consumption are statistically insignificant. This finding is in line with the main results reported in Table 1. Figure 2 also shows that there is no substantial evidence of a violation of the parallel trends assumption for the TSDID models, though there is one lead (-3) that rises to the level of statistical significance for two out of five outcomes (the probability of drinking alcohol and engaging in binge drinking).

We document similar results for females and males in Figures 3 and 4. Consistent with the results reported in Table 2, the long-run effects of UPPLs on alcohol consumption are mostly statistically insignificant in TSDID models for both females and males. The coefficients for the majority of lead terms are also statistically insignificant except for one statistically significant lead term (-3) in some outcomes.

5.2 Driving under the influence, alcohol-related traffic fatalities, and alcohol-related crimes

Table 6 shows that for those who reported consuming alcohol at least once in a given month, the UPPLs have a significant impact on drunk driving habits at the intensive margin. For the main sample, prohibiting alcohol exclusion provisions in the UPPLs is associated with up to a 0.072-time increase in the number of times that the respondent reported driving per month after drinking too much. This is a statistically significant and considerable increase relative to the mean of this outcome variable (0.099). A slightly larger impact is also observed for males.

Since BRFSS reports drunk driving outcomes for those who consumed alcohol at least once in a given month, we investigate whether the effects of the UPPLs on alcohol consumption behavior differ for this group of respondents who are expected to be affected by the changes in the UPPLs the most. We report the findings from this analysis in Appendix Table A7. Compared with the results reported in Tables 1 to 3, the estimated effects of prohibiting exclusion provisions in the UPPLs are larger for those who consume alcohol at least once in a given month. However, the estimated effects of the policy change remain statistically insignificant.

Table 7 shows that changes in drunk driving habits due to UPPLs do not lead to increased alcohol-related traffic fatalities. Results from both the TWFE and TSDID models show that the effect of prohibiting alcohol consumption provisions on different indicators of alcohol-related traffic fatality outcomes is small and statistically insignificant. Similarly, states without any UPPL related laws do not experience statistically different alcohol-related traffic fatality outcomes compared with the states with UPPLs.

Figures 5 to 7 illustrate the dynamic effects of the effect of prohibiting alcohol consumption provisions in the UPPLs on various drunk driving and alcohol-related traffic fatality outcomes. In Figure 5, there is no evidence of pre-existing trends in the BRFSS sample as all the lead terms are statistically insignificant. The long-term effects of the UPPLs on the number of times that the respondent reported driving after drinking too much are observed in the long run, specifically three periods after the policy change. We document similar results for different subsamples in Figure 6.

Figure 7 shows that there is no evidence of a violation of the parallel trends assumption in the FARS sample since all the lead terms are statistically insignificant in both TWFE and TSDID models. Consistent with our findings reported in Table 7, Figure 7 also illustrates that the effect of prohibiting alcohol exclusion provisions in the UPPLs on alcohol and drug-related traffic fatalities is insignificant.

Table 8 shows that the effect of prohibiting alcohol exclusion provisions in the UPPLs on alcohol-related crimes such as DUI, public drunkenness, and liquor law violation arrests is limited and statistically insignificant under the TSDID models. Figure 8 also illustrates these findings and shows that post-policy effects of prohibiting alcohol exclusion provisions on alternative indicators of alcohol-related crimes are insignificant.

5.3 Health insurance coverage and premiums

The effect of prohibiting alcohol exclusion provisions in the UPPLs on health insurance providers is unclear. On the one hand, it is plausible that prohibiting alcohol exclusion provisions increases the cost of insurance providers since they are now required to honor health insurance claims even if the patient is under the influence of alcohol or drugs. This may lead to an increase in health insurance premiums and a decrease in health insurance coverage rates. On the other hand, competition among the providers may prevent increases in health insurance premiums even if alcohol exclusion provisions are prohibited. We investigate whether UPPLs have any impact on health insurance coverage rates and premiums are report our findings in Tables 9 and 10. The results from the BRFSS sample show that the estimated impacts of prohibiting alcohol exclusion provisions on health insurance coverage rates among different population groups are close to zero and always statistically insignificant under the TSDID model. Our estimate for the full sample from this model (-0.002 with a standard error of 0.009) allows us to rule out, with 95% confidence, policy-induced increases in the probability of having health insurance coverage of more than 1.9 percent compared with the mean of this variable.

Similarly, the probability of having health insurance in states without any UPPLs are not statistically different than the states with the UPPLs. Although our BRFSS sample excludes those who are 65 and older (those who are eligible for Medicare), some of the respondents who reported having health insurance may still be covered by a public insurance plan such as Medicaid, which does not include any UPPL-related provisions. However, in Table 10, the results that are based on state-level data also support our findings and show that there is no significant association between UPPLs and private health insurance coverage rates.

The remainder of Table 10 reports results regarding the effect of the UPPLs on both the average dollar value and annual growth rate of health insurance premiums per enrolled employee at private-sector establishments that offer health insurance. Our findings show that the UPPLs do not have a statistically significant impact on these outcomes.

6 Conclusion

Alcohol exclusion provisions, which are part of the UPPL, allow health insurance providers to deny claims due to intoxication. Although these laws were originally proposed to discourage excessive drinking and substance use, there is no clear evidence that shows that they achieved their intended purpose. Furthermore, few studies document that these laws may have unintended consequences, as they create a disincentive for physicians to test the BAC levels of injured patients due to concerns about potential insurance reimbursement denials. The literature on the effectiveness of the UPPLs is very limited and has several shortcomings. In this paper, we provide a comprehensive analysis of the UPPLs by investigating their impact on alcohol consumption at the intensive and extensive margin, drunk driving behavior, alcohol-related traffic fatalities, alcohol-related crime, and health insurance coverage rates and premiums.

Major stakeholders such as the NAIC and APHA recommended the repeal of the UPPLs more than two decades ago. Since then, several states repealed their UPPLs. The existing evidence also favors the repeal of these laws as it shows that these laws may have negative effects on alcohol use disorder (AUD) treatments (Azagba, et al., 2022b and Azagba, et al., 2024) and reduce alcohol screening in emergency departments and trauma centers, which may hurt both patient outcomes and resource allocation (Chezem, 2004 and O'Keefe, et al, 2009). However, as of 2022, there are still 23 states with these laws.

Our findings based on data from multiple sources and the generalized difference-in-differences approach that is robust to treatment effect heterogeneity when adoption of the treatment is staggered suggest that UPPLs do not have a meaningful effect on alcohol consumption and the majority of alcohol consumption related outcomes. These effects are robust under alternative model specifications and several falsification tests. Using dynamic TWFE and TSDID models, we also document that for the full sample, the statistically insignificant effects of UPPLs on various outcomes are persistent both in the short and long run.

Our findings are particularly important given the ongoing public policy debates about the relevancy and effectiveness of the UPPLs. In general, our results confirm and complement those from Azagba, S., et al. (2022a), who find that alcohol exclusion provisions in the UPPLs do not have a statistically significant impact on alcohol consumption at the intensive margin. We document that this result also holds for alcohol consumption at the extensive margin. These findings suggest that UPPLs did not achieve their intended purpose of reducing alcohol consumption. Furthermore, except for their limited negative impact on the drunk driving behavior of those who drink at least once per month, we are the first to document that these laws have no impact on alcohol and drug-related traffic fatalities and alcohol-related crimes. We argued that other potential unintended consequences of removing alcohol exclusion provisions in the UPPLs would be an increase in health insurance premiums and a decrease in health insurance coverage rates. However, our results indicate that this is not the case and there is no statistically significant association between UPPLs and health insurance coverage rates and premiums. Therefore, our findings also favors the repeal of alcohol exclusion provisions in the UPPLs.

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[29] Substance Abuse and Mental Health Services Administration, 2019b, 2019 National survey on drug use and health detailed tables: Table 5.4A—Alcohol use disorder in past year among persons aged 12 or older, by age group and demographic characteristics: Numbers in Thousands, 2018, 2019.

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Table 1. The effect of the UPPLs on alcohol consumption

	TWFE		TSDID	
	(1)	(2)	(1)	(2)
Consumed alcohol				
Prohibit	-0.013**	0.002	0.008	0.025
	(0.006)	(0.004)	(0.017)	(0.016)
No Law	0.021	-0.006	0.136***	0.143***
	(0.023)	(0.005)	(0.035)	(0.054)
No. of Obs.	4858453	4251843	4858453	4251843
Sample mean	0.578	0.594	0.578	0.594
Engaged in binge drinking				
Prohibit	0.001	0.006**	0.005	0.001
	(0.003)	(0.003)	(0.005)	(0.006)
No Law	0.010	0.001	0.055***	0.003
	(0.008)	(0.004)	(0.014)	(0.027)
No. of Obs.	4810403	4215864	4810403	4215864
Sample mean	0.181	0.188	0.181	0.188
No. of days consumed alcohol				
Prohibit	-0.159	0.009	0.084	0.111
	(0.112)	(0.057)	(0.205)	(0.123)
No Law	0.131	-0.007	1.248***	0.719
	(0.227)	(0.066)	(0.342)	(0.809)
No. of Obs.	4839573	4237887	4839573	4237887
Sample mean	4.677	4.854	4.677	4.854
No. of days engaged in binge drinking				
Prohibit	-0.019	-0.001	-0.007	-0.035
	(0.017)	(0.010)	(0.025)	(0.030)
No Law	0.015	-0.020	0.167***	-0.090
	(0.049)	(0.018)	(0.056)	(0.161)
No. of Obs.	4810403	4215864	4810403	4215864
Sample mean	0.719	0.745	0.719	0.745
Average number of drinks per day				
Prohibit	-0.031	-0.001	-0.009	0.020
	(0.021)	(0.009)	(0.021)	(0.025)
No Law	0.009	0.008	0.081***	0.176
	(0.021)	(0.010)	(0.027)	(0.162)
No. of Obs.	4799299	4208114	4799299	4208114
Sample mean	0.422	0.438	0.422	0.438
Controls	No	Yes	No	Yes

Notes: Sample includes those who are under 65 and have health insurance coverage. All models include state and month-year fixed effects and are estimated using sample weights. "Controls" includes a full set of individual and state level control variables as discussed in the text. Standard errors, corrected for clustering at the state level, are reported in parentheses. The signs ** and *** represent statistical significance at 5 and 1 percent significance levels, respectively.

Table 2. The effect of the UPPLs on alcohol consumption by gender

	TWFE		TSDID	
	Female	Male	Female	Male
Consumed alcohol				
Prohibit	0.005	0.000	0.030*	0.021
	(0.005)	(0.005)	(0.016)	(0.017)
No Law	-0.005	-0.008	0.171***	0.115**
	(0.005)	(0.006)	(0.056)	(0.058)
No. of Obs.	2446175	1805325	2446175	1805325
Sample mean	0.538	0.651	0.538	0.651
Engaged in binge drinking				
Prohibit	0.008***	0.004	0.004	-0.001
	(0.002)	(0.004)	(0.006)	(0.008)
No Law	0.005	-0.003	0.008	0.002
	(0.004)	(0.005)	(0.033)	(0.035)
No. of Obs.	2429039	1786488	2429039	1786488
Sample mean	0.126	0.251	0.126	0.251
No. of days consumed alcohol				
Prohibit	0.023	-0.006	0.090	0.142
	(0.056)	(0.069)	(0.133)	(0.134)
No Law	0.048	-0.055	0.663	0.841
	(0.058)	(0.085)	(0.861)	(0.834)
No. of Obs.	2438583	1798961	2438583	1798961
Sample mean	3.658	6.080	3.658	6.080
No. of days engaged in binge drinking				
Prohibit	0.029**	-0.032*	0.016	-0.084
	(0.011)	(0.018)	(0.021)	(0.051)
No Law	0.047**	-0.085**	0.058	-0.222
	(0.022)	(0.033)	(0.149)	(0.267)
No. of Obs.	2429039	1786488	2429039	1786488
Sample mean	0.398	1.101	0.398	1.101
Average number of drinks per day				
Prohibit	0.004	-0.005	0.030	0.010
	(0.007)	(0.014)	(0.019)	(0.036)
No Law	0.013**	0.003	0.220**	0.137
	(0.006)	(0.016)	(0.106)	(0.227)
No. of Obs.	2424970	1782808	2424970	1782808
Sample mean	0.257	0.624	0.257	0.624

Notes: Sample includes those who are under 65 and have health insurance coverage. All models include state and month-year fixed effects, individual and state level controls as discussed in the text and are estimated using sample weights. Standard errors, corrected for clustering at the state level, are reported in parentheses. The signs *, **, and *** represent statistical significance at 10, 5, and 1 percent significance levels.

Table 3. The effect of the UPPLs on alcohol consumption by different age groups

	21-35 year olds		36-50 year olds		51-64 years old	
	TWFE	TSDID	TWFE	TSDID	TWFE	TSDID
Consumed alcohol						
Prohibit	0.001	0.012	0.007	0.040*	0.003	0.025
	(0.005)	(0.014)	(0.005)	(0.023)	(0.006)	(0.017)
No Law	-0.011	0.058	0.002	0.215***	-0.006	0.147***
	(0.009)	(0.051)	(0.005)	(0.075)	(0.004)	(0.057)
No. of Obs.	912958	912958	1476835	1476835	1774437	1774437
Sample mean	0.650	0.650	0.608	0.608	0.547	0.547
Engaged in binge drinking						
Prohibit	0.009*	0.003	0.006	0.003	0.003	-0.004
	(0.005)	(0.010)	(0.004)	(0.008)	(0.003)	(0.006)
No Law	0.003	-0.006	0.003	0.008	-0.000	0.005
	(0.007)	(0.044)	(0.005)	(0.032)	(0.003)	(0.024)
No. of Obs.	905004	905004	1464411	1464411	1759498	1759498
Sample mean	0.269	0.269	0.175	0.175	0.114	0.114
No. of days consumed alcohol						
Prohibit	-0.040	0.002	0.023	0.157	0.009	0.127
	(0.062)	(0.124)	(0.072)	(0.171)	(0.100)	(0.163)
No Law	0.039	0.255	0.147	0.675	-0.382**	0.994
	(0.092)	(0.842)	(0.123)	(1.120)	(0.189)	(0.823)
No. of Obs.	910713	910713	1471603	1471603	1768179	1768179
Sample mean	4.744	4.744	4.895	4.895	5.323	5.323
No. of days engaged in binge drinking						
Prohibit	-0.002	-0.031	-0.013	-0.022	0.011	-0.065
	(0.023)	(0.042)	(0.017)	(0.044)	(0.020)	(0.053)
No Law	-0.032	-0.150	0.007	0.049	0.004	-0.315*
	(0.034)	(0.257)	(0.018)	(0.214)	(0.019)	(0.182)
No. of Obs.	905004	905004	1464411	1464411	1759498	1759498
Sample mean	1.002	1.002	0.683	0.683	0.517	0.517
Average number of drinks per day						
Prohibit	-0.013	0.006	0.006	0.030	-0.006	-0.006
	(0.014)	(0.033)	(0.008)	(0.027)	(0.012)	(0.019)
No Law	0.013	0.162	0.016**	0.191	0.007	0.050
	(0.017)	(0.207)	(0.007)	(0.152)	(0.016)	(0.120)
No. of Obs.	902707	902707	1461939	1461939	1757055	1757055
Sample mean	0.496	0.496	0.422	0.422	0.404	0.404

Notes: All models include state and month-year fixed effects, individual and state level controls as discussed in the text and are estimated using sample weights. Standard errors, corrected for clustering at the state level, are reported in parentheses. The signs *, **, and *** represent statistical significance at 10, 5, and 1 percent significance levels.

Table 4. The effect of the UPPLs on alcohol consumption: Robustness checks

	Drop certain time periods (MD, ME, NJ)		Drop no-law states		Drop post-COVID period		Drop after 2011	
	TWFE	TSDID	TWFE	TSDID	TWFE	TSDID	TWFE	TSDID
Consumed alcohol								
Prohibit	0.002	0.026	0.003	0.025	0.002	0.025*	0.002	0.028
	(0.004)	(0.016)	(0.004)	(0.016)	(0.004)	(0.015)	(0.006)	(0.026)
No Law	-0.006	0.146***			-0.007	0.147**	-0.012*	0.251*
	(0.005)	(0.054)			(0.005)	(0.058)	(0.006)	(0.150)
No. of Obs.	4176272	4176272	3316848	3316848	3891060	3891060	1977412	1977412
Sample mean	0.593	0.593	0.588	0.589	0.594	0.595	0.593	0.593
Engaged in binge drinking								
Prohibit	0.006**	0.001	0.003	0.001	0.006**	-0.001	0.002	0.007
	(0.003)	(0.006)	(0.002)	(0.006)	(0.003)	(0.008)	(0.003)	(0.014)
No Law	0.001	0.004			-0.000	-0.012	-0.012	0.114
	(0.004)	(0.028)			(0.004)	(0.035)	(0.008)	(0.080)
No. of Obs.	4140854	4140854	3288164	3288164	3858806	3858806	1960183	1960183
Sample mean	0.188	0.188	0.184	0.184	0.187	0.188	0.176	0.176
No. of days consumed alcohol								
Prohibit	0.000	0.114	0.052	0.111	0.014	0.106	0.050	0.276
	(0.059)	(0.124)	(0.088)	(0.123)	(0.055)	(0.113)	(0.072)	(0.270)
No Law	-0.008	0.745			-0.040	0.531	-0.160*	2.159
	(0.066)	(0.817)			(0.060)	(0.851)	(0.085)	(1.838)
No. of Obs.	4162430	4162430	3305600	3305600	3877104	3877104	1963480	1963480
Sample mean	4.848	4.848	4.786	4.786	4.825	4.826	4.661	4.661
No. of days engaged in binge drinking								
Prohibit	-0.002	-0.035	-0.009	-0.035	0.004	-0.028	0.006	0.022
	(0.011)	(0.031)	(0.010)	(0.030)	(0.011)	(0.032)	(0.014)	(0.082)
No Law	-0.020	-0.096			-0.026*	-0.084	-0.056*	0.337
	(0.018)	(0.163)			(0.015)	(0.181)	(0.033)	(0.613)
No. of Obs.	4140854	4140854	3288164	3288164	3858806	3858806	1960183	1960183
Sample mean	0.744	0.744	0.729	0.729	0.785	0.786	0.669	0.669
Average number of drinks per day								
Prohibit	-0.002	0.020	-0.002	0.020	0.004	0.022	0.015	0.071
	(0.010)	(0.025)	(0.012)	(0.025)	(0.011)	(0.029)	(0.019)	(0.067)
No Law	0.008	0.180			0.009	0.165	-0.020	0.749*
	(0.010)	(0.166)			(0.009)	(0.184)	(0.020)	(0.438)
No. of Obs.	4133221	4133221	3281918	3281918	3851447	3851447	1952621	1952621
Sample mean	0.437	0.437	0.431	0.431	0.435	0.436	0.411	0.411

Notes: Sample includes those who are under 65 and have health insurance coverage. All models include state and month-year fixed effects, individual and state level controls as discussed in the text and are estimated using sample weights. Standard errors, corrected for clustering at the state level, are reported in parentheses. The signs *, **, and *** represent statistical significance at 10, 5, and 1 percent significance levels.

Table 5. The effect of the UPPLs on alcohol consumption: Stacked DID results

	Main sample
Consumed alcohol	
Prohibit	0.001
	(0.004)
No. of Obs.	23130794
Sample mean	0.583
Engaged in binge drinking	
Prohibit	0.004*
	(0.002)
No. of Obs.	22927999
Sample mean	0.183
No. of days consumed alcohol	
Prohibit	-0.021
	(0.060)
No. of Obs.	23054877
Sample mean	4.723
No. of days engaged in binge drinking	
Prohibit	-0.005
	(0.010)
No. of Obs.	22927999
Sample mean	0.733
Average number of drinks per day	
Prohibit	-0.010
	(0.012)
No. of Obs.	22882868
Sample mean	0.430

Notes: Main sample includes those who are under 65 and have health insurance coverage. All models include stack, state, and month-year fixed effects, and individual and state level controls as discussed in the text and are estimated using sample weights. Standard errors, corrected for clustering at the state level, are reported in parentheses. The signs * and ** represent statistical significance at 5 and 1 percent significance levels.

Table 6. The effect of the UPPLs on drunk driving outcomes: BRFSS samples

	TWFE			TSDID		
	Main sample	Female	Male	Main sample	Female	Male
Engaged in drunk driving						
Prohibit	0.007***	0.006***	0.008***	0.005	0.004	0.006
	(0.002)	(0.001)	(0.002)	(0.004)	(0.003)	(0.005)
No Law	-0.001	0.000	-0.001	-0.012	-0.016	-0.006
	(0.003)	(0.002)	(0.004)	(0.015)	(0.016)	(0.023)
No. of Obs.	1273251	681262	591866	1273251	681262	591866
Sample mean	0.039	0.023	0.053	0.039	0.023	0.053
No. of times drink and drive						
Prohibit	0.055**	0.048**	0.062**	0.072**	0.054	0.092**
	(0.021)	(0.020)	(0.024)	(0.035)	(0.034)	(0.038)
No Law	-0.016	-0.011	-0.022	0.096	0.026	0.173
	(0.032)	(0.026)	(0.037)	(0.066)	(0.051)	(0.129)
No. of Obs.	1273251	681262	591866	1273251	681262	591866
Sample mean	0.099	0.052	0.140	0.099	0.052	0.140

Notes: All samples include those who have health insurance coverage and consumed alcohol at least once in the past month. Main, female, and male samples include those who are under 65. All models include state and month-year fixed effects, individual and state level controls as discussed in the text and are estimated using sample weights. Standard errors, corrected for clustering at the state level, are reported in parentheses. The signs *, **, and *** represent statistical significance at 10, 5, and 1 percent significance levels.

Table 7. The effect of the UPPLs on traffic fatalities due to intoxication: FARS sample

	TWFE	TSDID
Share of under-the-influence drivers		
Prohibit	0.006	0.013
	(0.009)	(0.050)
No Law	0.029**	-0.021
	(0.013)	(0.132)
No. of Obs.	14650	14650
Sample mean	0.189	0.189
No. of under-the-influence drivers		
Prohibit	0.025*	-0.052
	(0.014)	(0.095)
No Law	0.044*	-0.299
	(0.024)	(0.259)
No. of Obs.	14650	14650
Sample mean	0.296	0.296

Notes: All models include state and month-year fixed effects and state level controls as discussed in the text. Standard errors, corrected for clustering at the state level, are reported in parentheses. The signs * and ** represent statistical significance at 10 and 5 percent significance levels.

Table 8. The effect of the UPPLs on alcohol consumption related crimes: NIBRS sample

	TWFE	TSDID
Share of DUI arrests		
Prohibit	0.070***	-0.199
	(0.022)	(0.142)
No Law	0.056***	-0.412*
	(0.016)	(0.210)
No. of Obs.	9671	9671
Sample mean	0.210	0.211
Share of public drunkenness arrests		
Prohibit	0.013	-0.153
	(0.009)	(0.097)
No Law	0.017**	-0.190
	(0.008)	(0.142)
No. of Obs.	9671	9671
Sample mean	0.059	0.059
Share of liquor law violation arrests		
Prohibit	-0.020*	0.014
	(0.010)	(0.060)
No Law	-0.037***	0.029
	(0.011)	(0.096)
No. of Obs.	9671	9671
Sample mean	0.091	0.091

Notes: All models include state and month-year fixed effects and state level controls as discussed in the text. Standard errors, corrected for clustering at the state level, are reported in parentheses. The signs *, **, and *** represent statistical significance at 10, 5, and 1 percent significance levels.

Table 9. The effect of the UPPLs on health insurance coverage: BRFSS sample

	TWFE			TSDID		
	Main sample	Female	Male	Main sample	Female	Male
Has health insurance coverage						
Prohibit	-0.004	-0.001	-0.008*	-0.002	0.003	-0.007
	(0.004)	(0.004)	(0.004)	(0.009)	(0.010)	(0.010)
No Law	-0.011**	-0.012**	-0.010**	-0.044	-0.046	-0.044
	(0.005)	(0.005)	(0.005)	(0.038)	(0.044)	(0.039)
No. of Obs.	5183123	2954644	2228041	5183123	2954644	2228041
Sample mean	0.837	0.851	0.822	0.837	0.851	0.822

Notes: Main, female, and male samples include those who are under 65. All models include state and month-year fixed effects, individual and state level controls as discussed in the text and are estimated using sample weights. Standard errors, corrected for clustering at the state level, are reported in parentheses. The sign ** represents statistical significance at 5 percent significance level.

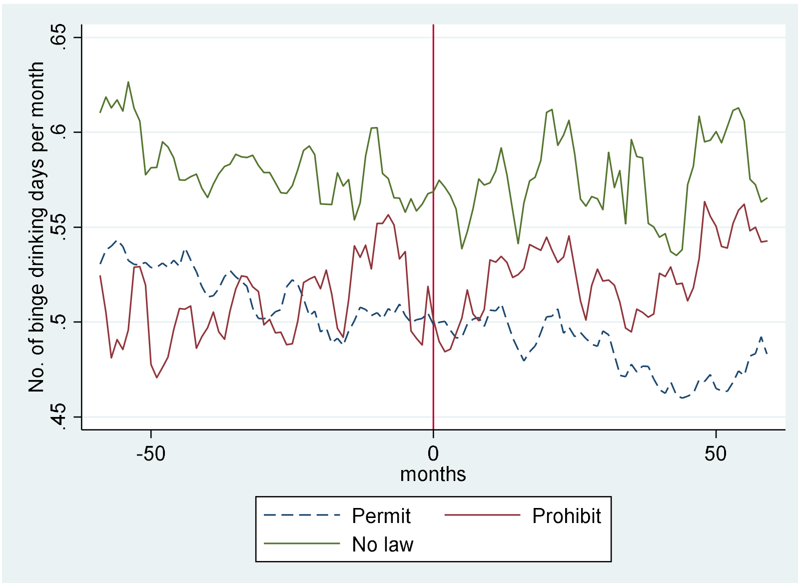
Table 10. The effect of the UPPLs on health insurance coverage rates and health insurance premiums: MEPS-IC sample

	TWFE	TSDID
Private health insurance coverage rate		
Prohibit	0.095	-0.635
	(0.306)	(1.603)
No Law	-0.518	-5.481
	(0.414)	(6.325)
No. of Obs.	1123	1123
Sample mean	51.078	51.078
Average health insurance total premium		
Prohibit	12.106	-144.660
	(61.763)	(172.941)
No Law	9.976	-206.290
	(58.801)	(522.459)
No. of Obs.	1123	1123
Sample mean	5871.10	5871.10
Annual change in health insurance total premium		
Prohibit	0.004	-0.019
	(0.005)	(0.018)
No Law	0.004	-0.094*
	(0.005)	(0.054)
No. of Obs.	1085	1085
Sample mean	0.013	0.013

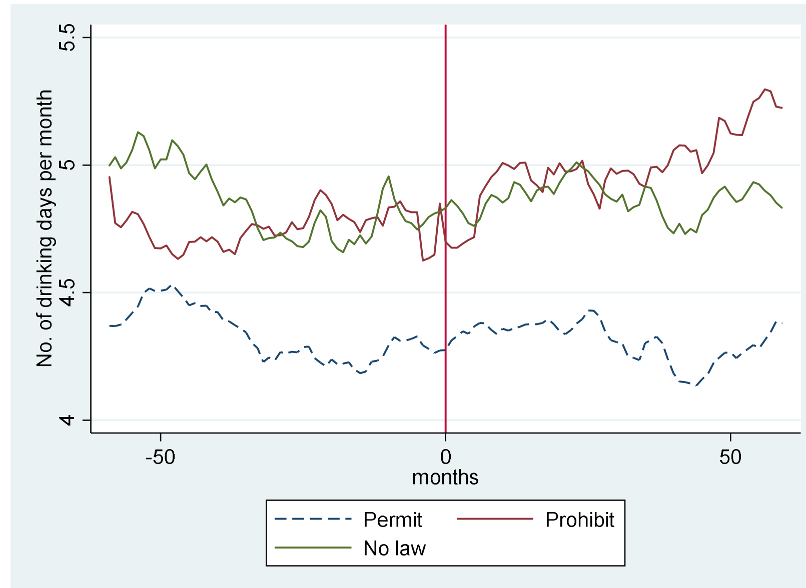
Notes: All models include state and year fixed effects and state level controls as discussed in the text. Standard errors, corrected for clustering at the state level, are reported in parentheses. The sign * represents statistical significance at 10 percent significance level.

Figure 1. Alcohol consumption trends based on the UPPL status

A. Binge drinking days per month

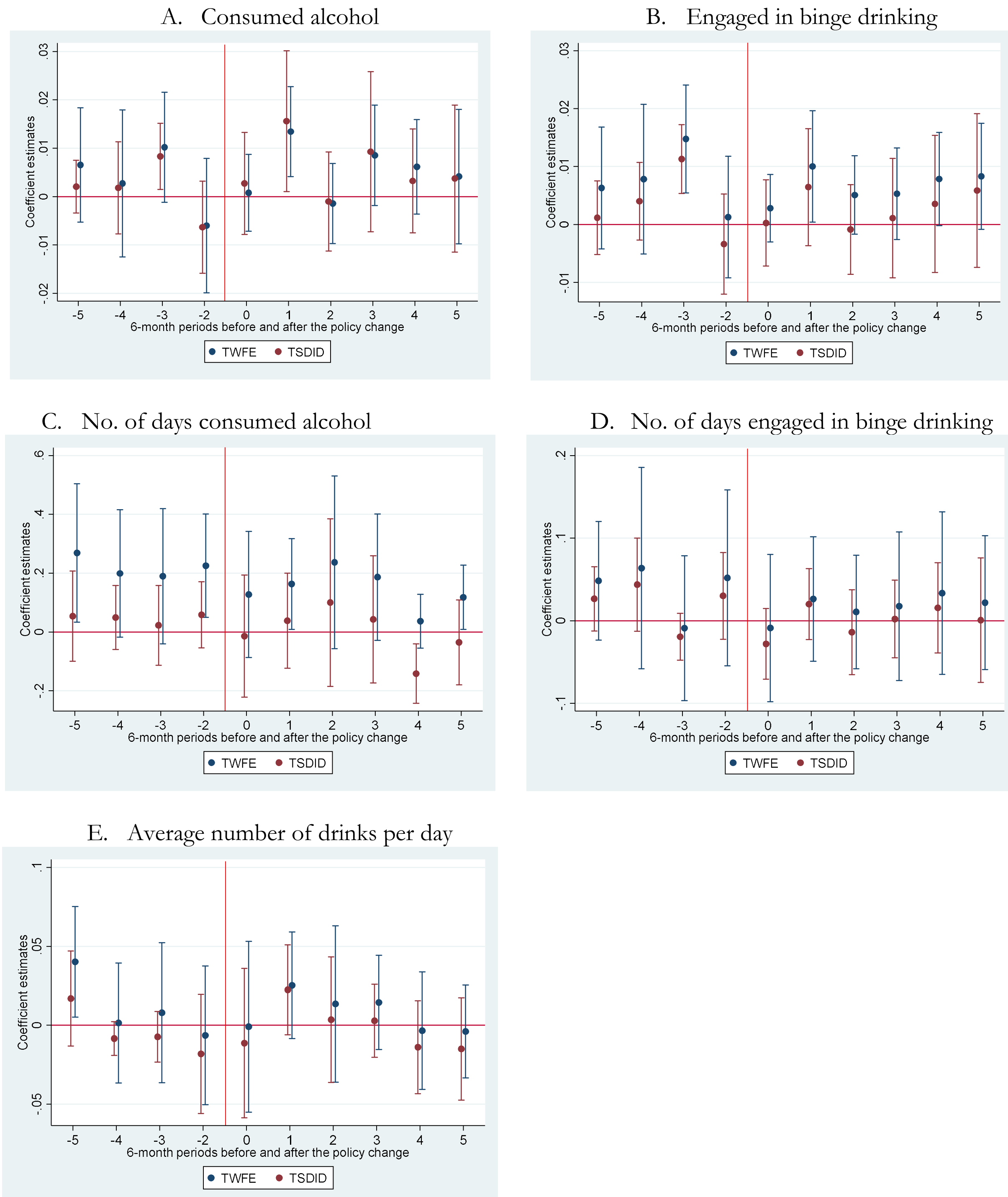


B. Drinking days per month



Notes: Mean alcohol consumption trends (equally-weighted 3-month moving averages) 60 months before and after the policy change (prohibiting denial of health insurance claims due to intoxication) are plotted.

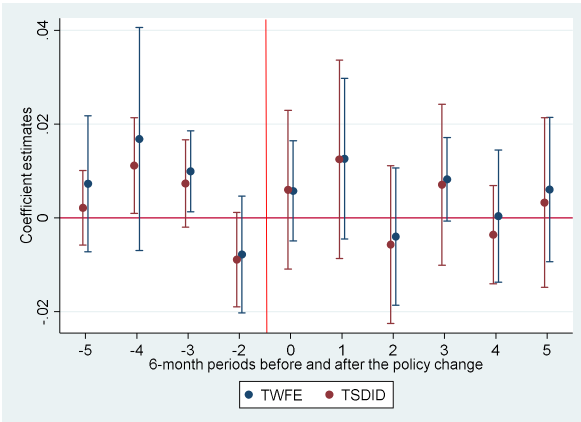
Figure 2. Dynamic TFWE and TSDID estimates of the effect of the UPPL on alcohol consumption: Main sample



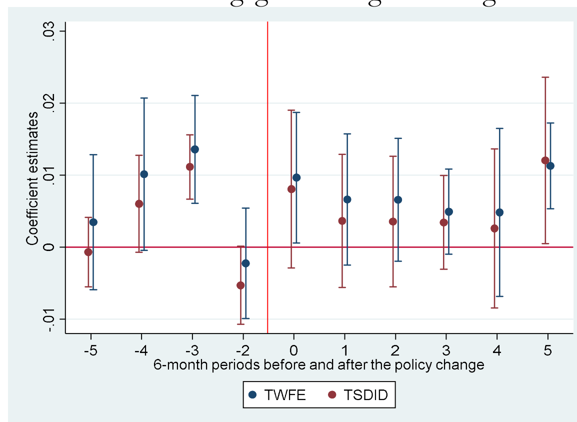
Notes: Dynamic effects of prohibiting denial of health insurance claims due to intoxication are reported. Although estimates for five periods are reported, the models include more periods that cover the entire analysis period. All models are estimated using sample weights and include full set of state and individual level controls, and state and month-year fixed effects as discussed in the text. The sample includes those who are under 65 and have health insurance coverage.

Figure 3. Dynamic TFWE and TSDID estimates of the effect of the UPPL on alcohol consumption: Females

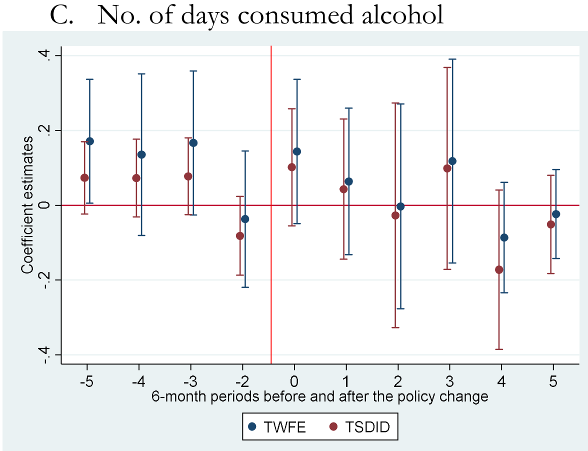
A. Consumed alcohol



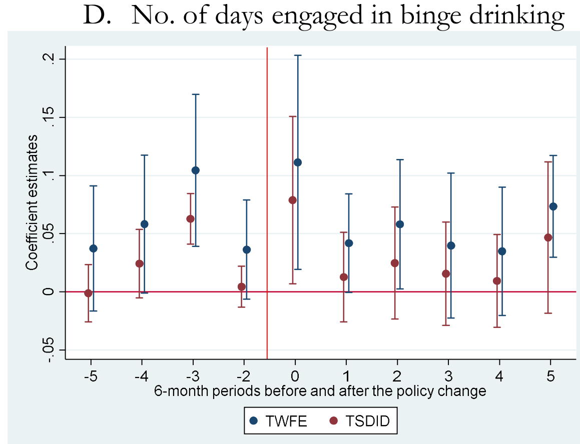
B. Engaged in binge drinking



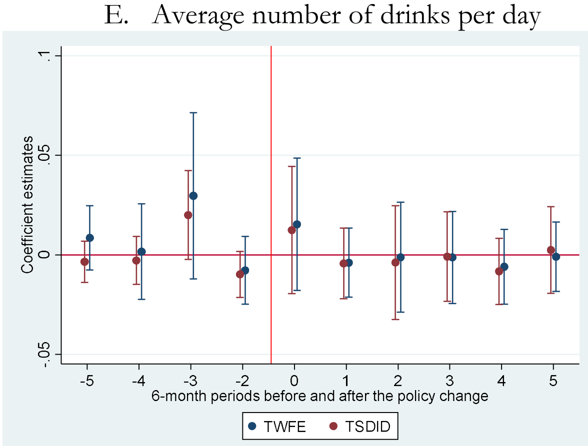
C. No. of days consumed alcohol



D. No. of days engaged in binge drinking



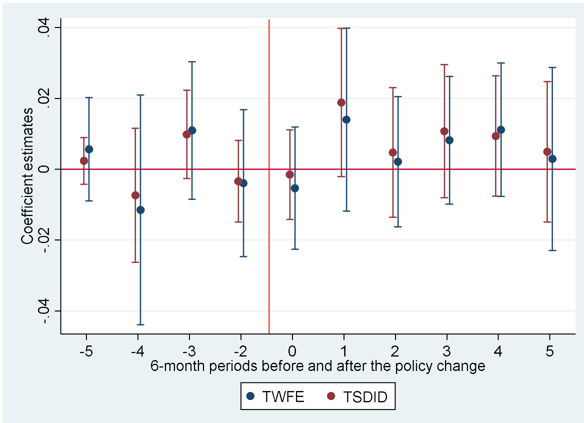
E. Average number of drinks per day



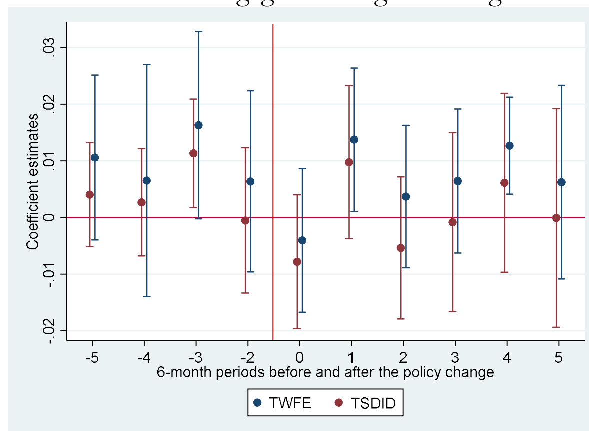
Notes: Dynamic effects of prohibiting denial of health insurance claims due to intoxication are reported. Although estimates for five periods are reported, the models include more periods that cover the entire analysis period. All models are estimated using sample weights and include full set of state and individual level controls, and state and month-year fixed effects as discussed in the text. The sample includes females who are under 65 and have health insurance coverage.

Figure 4. Dynamic TFWE and TSDID estimates of the effect of the UPPL on alcohol consumption: Males

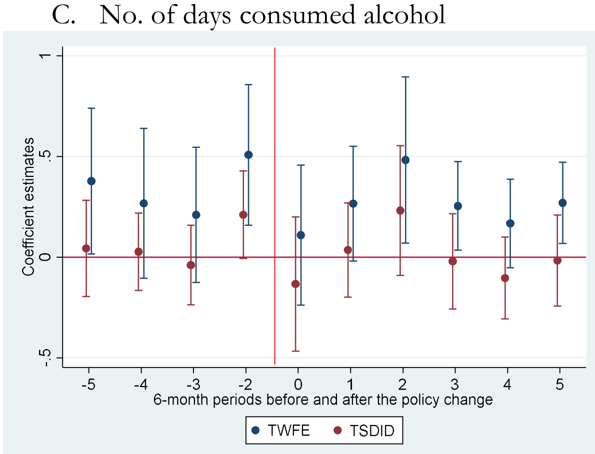
A. Consumed alcohol



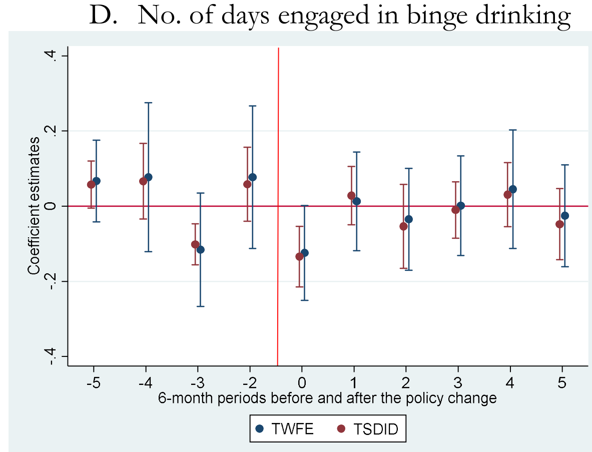
B. Engaged in binge drinking



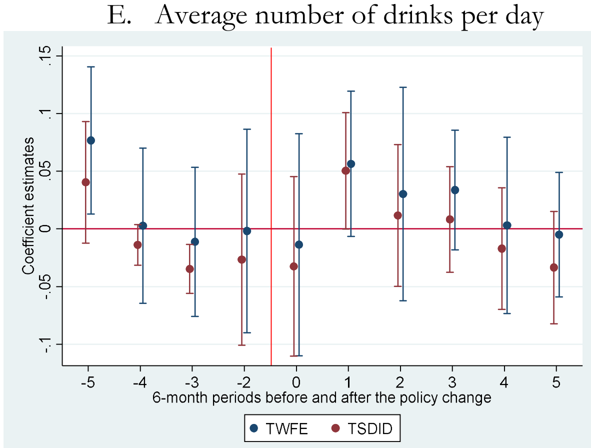
C. No. of days consumed alcohol



D. No. of days engaged in binge drinking



E. Average number of drinks per day

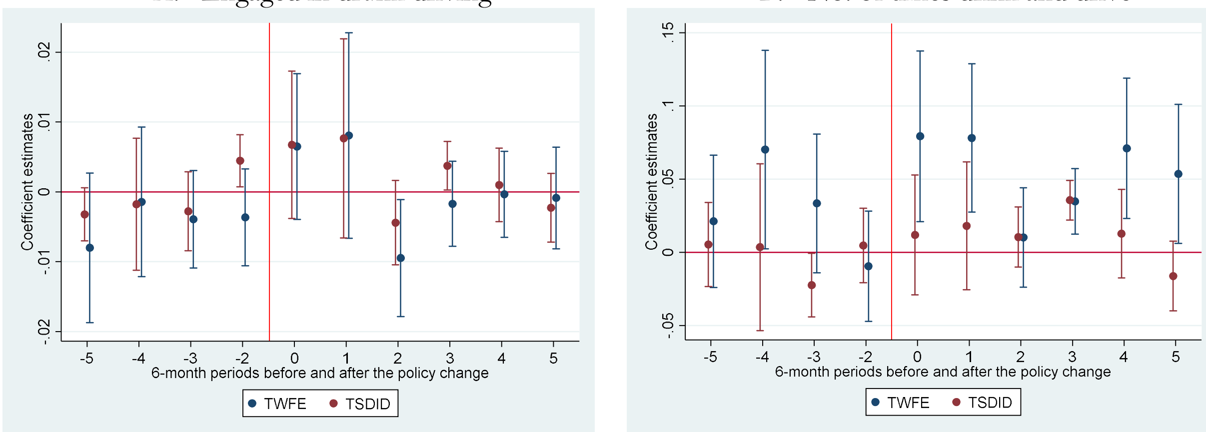


Notes: Dynamic effects of prohibiting denial of health insurance claims due to intoxication are reported. Although estimates for five periods are reported, the models include more periods that cover the entire analysis period. All models are estimated using sample weights and include full set of state and individual level controls, and state and month-year fixed effects as discussed in the text. The sample includes males who are under 65 and have health insurance coverage.

Figure 5. Dynamic TFWE and TSDID estimates of the effect of the UPPL on drunk driving outcomes: BRFSS main sample

A. Engaged in drunk driving

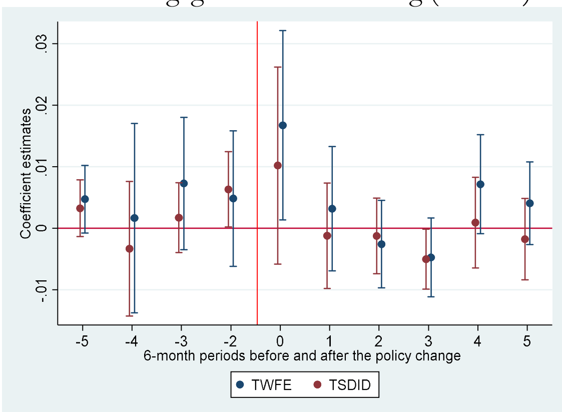
B. No. of times drink and drive



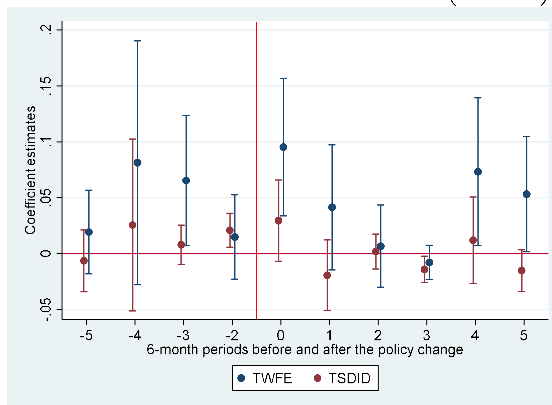
Notes: Dynamic effects of prohibiting denial of health insurance claims due to intoxication are reported. Although estimates for five periods are reported, the models include more periods that cover the entire analysis period. All models are estimated using sample weights and include full set of state and individual level controls, and state and month-year fixed effects as discussed in the text. The sample includes those who consumed alcohol at least once at a given month, are under 65, and have health insurance coverage.

Figure 6. Dynamic TFWE and TSDID estimates of the effect of the UPPL on drunk driving outcomes: BRFSS subsamples

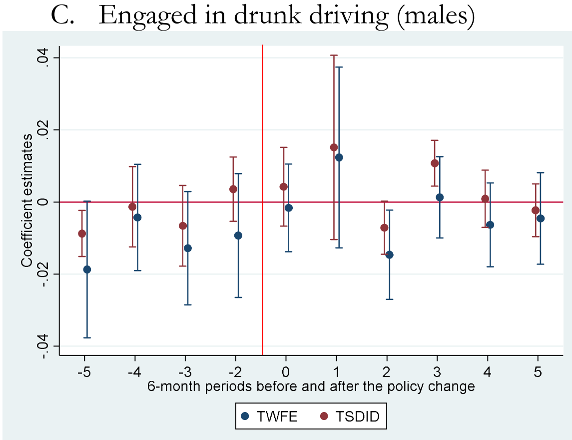
A. Engaged in drunk driving (females)



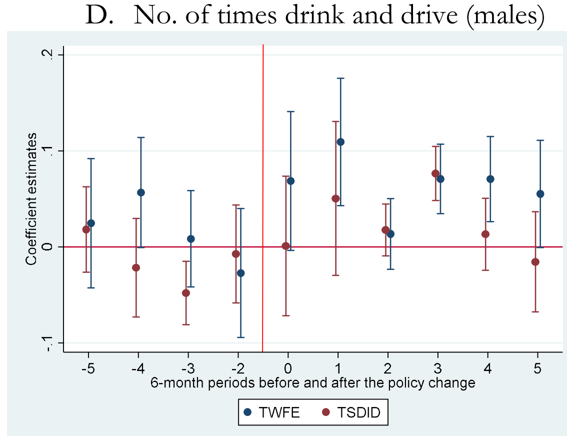
B. No. of times drink and drive (females)



C. Engaged in drunk driving (males)



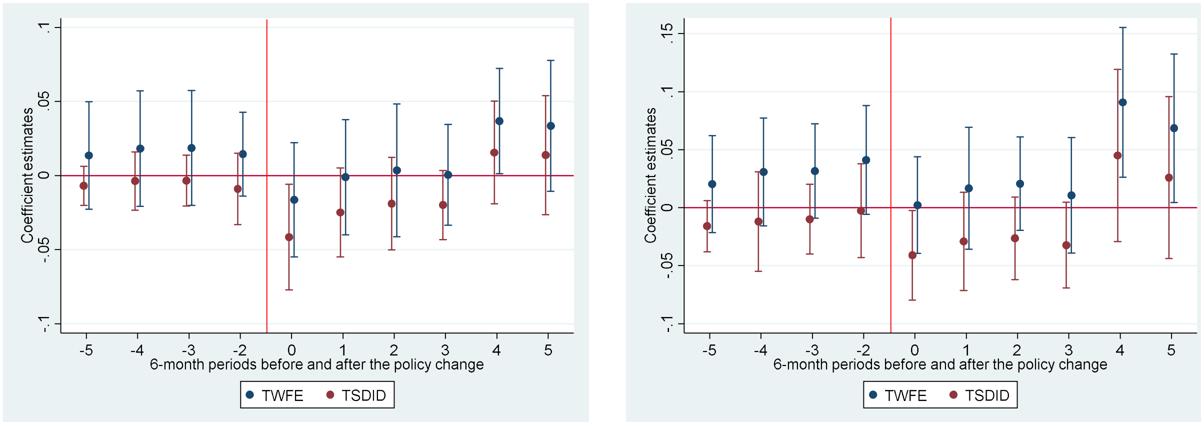
D. No. of times drink and drive (males)



Notes: Dynamic effects of prohibiting denial of health insurance claims due to intoxication are reported. Although estimates for five periods are reported, the models include more periods that cover the entire analysis period. All models are estimated using sample weights and include full set of state and individual level controls, and state and month-year fixed effects as discussed in the text. The sample includes those who consumed alcohol at least once at a given month, are under 65 (for males and females), and have health insurance coverage.

Figure 7. Dynamic TFWE and TSDID estimates of the effect of the UPPL on traffic fatalities due to intoxication: FARS sample

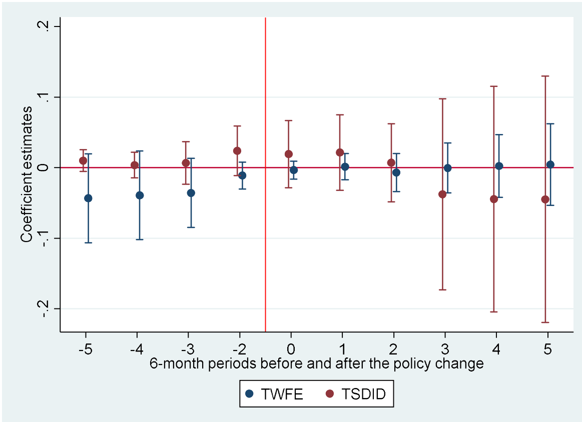
A. Share of under-the-influence drivers B. No. of under-the-influence drivers



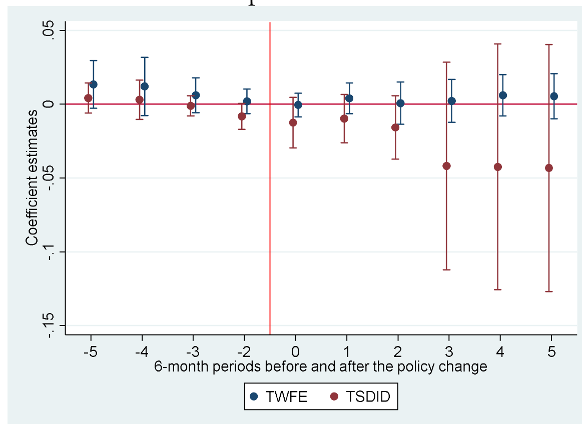
Notes: Dynamic effects of prohibiting denial of health insurance claims due to intoxication are reported. Although estimates for five periods are reported, the models include more periods that cover the entire analysis period. All models include a full set of state level controls, and state and month-year fixed effects as discussed in the text.

Figure 8. Dynamic TFWE and TSDID estimates of the effect of the UPPL on alcohol consumption related crimes: NIBRS sample

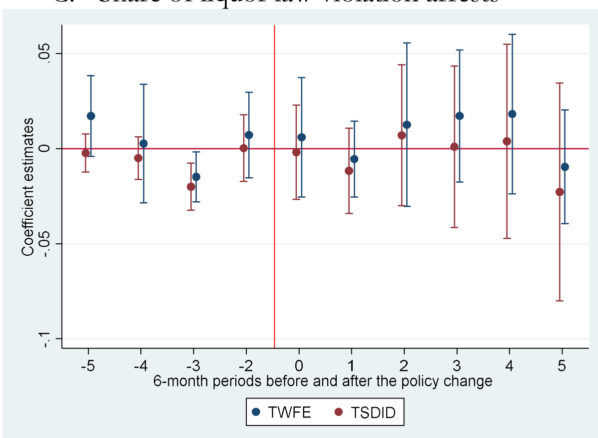
A. Share of DUI arrests



B. Share of public drunkenness arrests



C. Share of liquor law violation arrests



Notes: Dynamic effects of prohibiting denial of health insurance claims due to intoxication are reported. Although estimates for five periods are reported, the models include more periods that cover the entire analysis period. All models include a full set of state level controls, and state and month-year fixed effects as discussed in the text.

Appendix

Table A1. Enforcement dates of the UPPLs across states

States	Permit	Prohibit	No Law
Alabama	Yes		
Alaska	Yes		
Arizona	Yes		
Arkansas	Yes		
California	Until 12/31/2008	From 1/1/2009	
Colorado		From 1/1/2007	Until 12/31/2006
Connecticut		From 10/1/2006	Until 9/30/2006
Delaware	Yes		
District of Columbia	Until 3/7/2008	From 3/8/2007	
Florida	Yes		
Georgia	Yes		
Hawaii	Yes		
Idaho	Yes		
Illinois	Until 12/31/2007	From 1/1/2008	
Indiana	Until 12/31/2007	From 1/1/2008	
Iowa	Until 6/30/2002	From 7/1/2002	
Kansas	Yes		
Kentucky	Yes		
Louisiana	Yes		
Maine	Yes[a]		
Maryland	Until 10/29/2000	From 10/30/2000[b]	
Massachussets			Yes
Michigan			Yes
Minnesota			Yes
Mississippi	Yes		
Missouri	Yes		
Montana	Until 2/27/2019		From 2/28/2019
Nebraska	Yes		
Nevada	Until 6/30/2006	From 7/1/2006	
New Hampshire			Yes
New Jersey	Until 5/5/2019	From 5/6/2019[c]	
New Mexico			Yes
New York	Yes		
North Carolina	Until 9/30/2001	From 10/1/2001	
North Dakota	Until 7/31/2009	From 8/1/2009	
Ohio	Until 4/6/2009	From 4/7/2009	
Oklahoma			Yes
Oregon	Until 12/31/2007	1/1/2008 - 12/31/2017	From 1/1/2018
Pennsylvania	Yes		
Rhode Island	Until 6/15/2005	From 6/16/2005	
South Carolina	Yes		
South Dakota		Yes	
Tennessee	Until 6/30/2015		From 7/1/2015
Texas	Until 12/31/2013		From 1/1/2014
Utah			Yes
Vermont	Until 6/4/2002		From 6/5/2002
Virginia	Yes		
Washington	Until 6/9/2004	From 6/10/2004	
West Virginia	Yes		
Wisconsin			Yes
Wyoming	Yes		

Notes: "Yes" indicates that the policy was effective for the entire analysis period of 1998 – 2021. (a) In Maine, from September 20, 2007 until now, intoxication exclusions are prohibited in health insurance contracts with the exception that they are permitted in group or blanket policies. (b) In Maryland, between October 30, 2000 and December 31, 2001, intoxication exclusions were permitted by statute in individual health insurance policies but were prohibited by regulation in group health insurance policies, individual and group health maintenance contracts, and individual nonprofit health service plans. (c) In New Jersey, from May 6, 2019 until now, a blanket insurance policy or certificate or other group policy or certificate providing health insurance may include an exclusion for losses resulting from the covered person's use of alcohol, but this does not apply to a group health benefits plan.

Table A2. Description of outcome variables and summary statistics

Outcome	N	Mean	S.D.	Description
BRFSS Outcomes				
1. Consumed alcohol	4958045	0.575	0.494	=1 if the respondent consumed alcohol at least once in the past month, =0 otherwise.
2. Engaged in binge drinking	4908548	0.180	0.384	=1 if the respondent consumed 5 or more drinks at least in one day in the past month, =0 otherwise.
3. No. of days consumed alcohol	4938645	4.637	7.405	Number of days that the respondent consumed alcohol in the past month.
4. No. of days engaged in binge drinking	4908548	0.716	2.777	Number of days that the respondent consumed 5 or more drinks in the past month.
5. Average number of drinks per day	4896944	0.420	1.200	Average number of drinks that the respondent consumed per month. Calculated using information on the number of days that the respondent consumed alcohol and the number of drinks that the respondent consumed on those days.
6. Engaged in drunk driving	1438120	0.038	0.192	=1 if the respondent drove at least once in the past month after drinking too much, =0 otherwise. Sample includes those who drunk at least once last month.
7. No. of times drink and drive	1438120	0.105	0.967	Number of times that the respondent drove in the past month after drinking too much. Sample includes those who drunk at least once last month.
8. Has health insurance coverage	6157699	0.828	0.378	= 1 if the respondent reported having health insurance coverage, =0 otherwise.
FARS Outcomes				
9. Share of under-the-influence drivers	14,650	0.189	0.113	Total number of drivers under the influence divided by the total number of drivers (state-month level sample of all traffic accidents that resulted in a fatality).
10. No. of under-the-influence drivers	14,650	0.296	0.225	Number of under-the-influence drivers involved in fatal crashes per 100,000 people (state-month level sample of all traffic accidents that resulted in a fatality).
NIBRS Outcomes				
11. Share of DUI arrests	9,543	0.212	0.097	Share of DUI arrests among the total category B crimes.
12. Share of public drunkenness arrests	6,670	0.086	0.090	Share of public drunkenness arrests among the total category B crimes.
13. Share of liquor law violation arrests	9,386	0.094	0.081	Share of liquor law violation arrests among the total category B crimes.
MEPS IC Outcomes				
14. Private health insurance coverage rate	1123	51.08	5.011	Percent of private sector employees enrolled in a health insurance plan that take single coverage.
15. Average health insurance total premium	1123	5871.10	1172.42	Average total single premium (adjusted for 2021 prices) per enrolled employee at private-sector establishments that offer health insurance.
16. Annual change in health insurance total premium	1085	0.013	0.116	Annual percentage change in average total single premium (adjusted for 2021 prices) per enrolled employee at private-sector establishments that offer health insurance.

Notes: Mean and standard deviation (S.D.) of outcome variables are reported. The sample for all BRFSS outcomes with the exception of "Has health insurance coverage" is those who are younger than 65 and have health insurance coverage. The sample for "Has health insurance coverage" is those who are younger than 65.

Table A3. The effect of the UPPLs on alcohol consumption outcomes: TSDID estimates for the full BRFSS sample and for those who do not have health insurance coverage

	Full sample	Not covered by a health insurance plan
Consumed alcohol		
Prohibit	0.026*	0.030
	(0.015)	(0.021)
No Law	0.150***	0.190***
	(0.052)	(0.068)
No. of Obs.	6877740	641900
Sample mean	0.555	0.511
Engaged in binge drinking		
Prohibit	0.001	0.002
	(0.005)	(0.013)
No Law	0.014	0.108*
	(0.026)	(0.056)
No. of Obs.	6816873	632706
Sample mean	0.168	0.219
No. of days consumed alcohol		
Prohibit	0.157	-0.001
	(0.126)	(0.161)
No Law	1.050	0.450
	(0.757)	(1.016)
No. of Obs.	6852376	638678
Sample mean	4.773	4.006
No. of days engaged in binge drinking		
Prohibit	-0.041	-0.137
	(0.033)	(0.096)
No Law	-0.075	-0.253
	(0.185)	(0.502)
No. of Obs.	6816873	632706
Sample mean	0.710	0.219
Average number of drinks per day		
Prohibit	0.016	-0.038
	(0.027)	(0.070)
No Law	0.138	-0.120
	(0.164)	(0.339)
No. of Obs.	6801248	630552
Sample mean	0.431	0.543

Notes: All models include individual and state level controls, state, and month-year fixed effects and are estimated using sample weights. Standard errors, corrected for clustering at the state level, are reported in parentheses. The sign * represents statistical significance at 10 percent significance level.

Table A4. The effect of the UPPLs on alcohol consumption outcomes: Models that include state-specific linear time trends

	TWFE			TSDID		
	Main sample	Females	Males	Main sample	Females	Males
Consumed alcohol						
Prohibit	0.008	0.011	0.005	0.068*	0.029	0.106
	(0.006)	(0.008)	(0.007)	(0.039)	(0.034)	(0.070)
No Law	-0.001	0.002	-0.004	0.182	0.212	0.158
	(0.006)	(0.007)	(0.008)	(0.156)	(0.155)	(0.180)
No. of Obs.	4251843	2446175	1805325	4251843	2446175	1805325
Sample mean	0.594	0.538	0.651	0.594	0.538	0.651
Engaged in binge drinking						
Prohibit	0.006	0.011***	0.000	0.039	0.004	0.074
	(0.004)	(0.003)	(0.004)	(0.038)	(0.039)	(0.069)
No Law	0.011**	0.014***	0.009	0.039	0.134	-0.039
	(0.005)	(0.005)	(0.007)	(0.087)	(0.083)	(0.114)
No. of Obs.	4215864	2429039	1786488	4215864	2429039	1786488
Sample mean	0.188	0.126	0.251	0.188	0.126	0.251
No. of days consumed alcohol						
Prohibit	0.084	0.127*	0.039	0.459	0.141	0.855
	(0.083)	(0.069)	(0.109)	(0.501)	(0.588)	(1.057)
No Law	-0.025	-0.032	-0.022	0.145	1.118	-0.736
	(0.091)	(0.082)	(0.115)	(1.735)	(1.676)	(2.289)
No. of Obs.	4237887	2438583	1798961	4237887	2438583	1798961
Sample mean	4.854	3.658	6.080	4.854	3.658	6.080
No. of days engaged in binge drinking						
Prohibit	0.001	0.050***	-0.049*	0.008	0.339	-0.338
	(0.020)	(0.018)	(0.028)	(0.153)	(0.224)	(0.317)
No Law	0.016	0.053**	-0.020	-0.320	0.944**	-1.507
	(0.029)	(0.021)	(0.044)	(0.603)	(0.480)	(1.056)
No. of Obs.	4215864	2429039	1786488	4215864	2429039	1786488
Sample mean	0.745	0.398	1.101	0.745	0.398	1.101
Average number of drinks per day						
Prohibit	0.023	0.022*	0.023	0.109	0.134**	0.088
	(0.021)	(0.013)	(0.031)	(0.103)	(0.066)	(0.172)
No Law	0.012	0.006	0.018	0.461	0.746*	0.176
	(0.012)	(0.007)	(0.022)	(0.471)	(0.382)	(0.624)
No. of Obs.	4208114	2424970	1782808	4208114	2424970	1782808
Sample mean	0.438	0.257	0.624	0.438	0.257	0.624

Notes: Sample includes those who are under 65 and have health insurance coverage. All models include state and month-year fixed effects, state-specific linear time trends, individual and state level controls as discussed in the text and are estimated using sample weights. Standard errors, corrected for clustering at the state level, are reported in parentheses. The signs *, **, and *** represent statistical significance at 10, 5, and 1 percent significance levels.

Table A5. The effect of the UPPLs on alcohol consumption by household income

	Inc. < \$50K		\$50K ≤ Inc. < \$100K		\$100K ≤ Inc. < \$150K		\$150K ≤ Inc. < \$200K		Inc. ≥ \$200K	
	TWFE	TSDID	TWFE	TSDID	TWFE	TSDID	TWFE	TSDID	TWFE	TSDID
Consumed alcohol										
Prohibit	0.006	0.023*	0.002	0.017	0.004	0.037	-0.019	-0.071***	-0.052	-0.087**
	(0.006)	(0.013)	(0.005)	(0.017)	(0.004)	(0.027)	(0.091)	(0.018)	(0.109)	(0.037)
No Law	-0.003	0.137***	-0.012**	0.100	-0.002	0.195	0.006	-0.057	-0.028	0.017
	(0.007)	(0.049)	(0.005)	(0.068)	(0.005)	(0.120)	(0.055)	(0.035)	(0.075)	(0.054)
No. of Obs.	1492450	1492450	1906888	1906888	825089	825089	13911	13911	13505	13505
Sample mean	0.468	0.468	0.631	0.631	0.715	0.715	0.711	0.711	0.753	0.753
Engaged in binge drinking										
Prohibit	0.009**	0.008	0.006*	0.002	0.001	-0.006	0.056	-0.009	-0.004	-0.002
	(0.005)	(0.007)	(0.003)	(0.006)	(0.004)	(0.011)	(0.040)	(0.020)	(0.108)	(0.021)
No Law	0.002	0.031	-0.001	0.009	-0.004	-0.026	0.025	-0.001	0.006	0.045
	(0.006)	(0.033)	(0.004)	(0.032)	(0.009)	(0.063)	(0.024)	(0.026)	(0.074)	(0.029)
No. of Obs.	1476441	1476441	1892755	1892755	819478	819478	13796	13796	13394	13394
Sample mean	0.170	0.170	0.198	0.198	0.194	0.194	0.227	0.227	0.217	0.217
No. of days consumed alcohol										
Prohibit	-0.022	-0.007	0.031	-0.015	0.042	0.495	-2.672***	-0.036	-2.872	-2.076***
	(0.049)	(0.077)	(0.070)	(0.108)	(0.101)	(0.461)	(0.775)	(0.375)	(2.278)	(0.727)
No Law	0.011	0.442	-0.099	-0.395	0.010	3.486	-1.228***	-0.454	-1.310	-0.410
	(0.074)	(0.538)	(0.076)	(0.791)	(0.134)	(2.601)	(0.450)	(1.329)	(1.563)	(0.754)
No. of Obs.	1487685	1487685	1901717	1901717	821069	821069	13911	13911	13505	13505
Sample mean	3.386	3.386	5.252	5.252	6.321	6.321	6.653	6.653	7.439	7.439
No. of days engaged in binge drinking										
Prohibit	-0.006	0.014	0.011	-0.084	-0.013	-0.021	0.420**	-0.425*	0.471	-0.349
	(0.018)	(0.040)	(0.015)	(0.067)	(0.024)	(0.077)	(0.191)	(0.230)	(0.730)	(0.267)
No Law	-0.024	0.337	-0.016	-0.512**	-0.021	0.173	0.396***	0.001	0.357	0.274
	(0.032)	(0.238)	(0.018)	(0.250)	(0.037)	(0.531)	(0.115)	(0.118)	(0.504)	(0.220)
No. of Obs.	1476441	1476441	1892755	1892755	819478	819478	13796	13796	13394	13394
Sample mean	0.749	0.749	0.773	0.773	0.680	0.680	0.878	0.878	0.801	0.801

Average number of drinks per day										
Prohibit	-0.003	0.025	-0.004	-0.007	0.009	0.038	-0.263**	-0.211	0.282	-0.044
	(0.011)	(0.024)	(0.010)	(0.024)	(0.018)	(0.065)	(0.128)	(0.136)	(0.353)	(0.286)
No Law	0.024*	0.363**	-0.012	-0.037	0.012	0.325	-0.092	-0.081	0.204	0.139
	(0.012)	(0.178)	(0.011)	(0.132)	(0.024)	(0.453)	(0.070)	(0.121)	(0.243)	(0.164)
No. of Obs.	1473660	1473660	1889932	1889932	817362	817362	13769	13769	13391	13391
Sample mean	0.375	0.375	0.462	0.462	0.486	0.486	0.556	0.556	0.580	0.580

Notes: Sample includes those who are under 65 and have health insurance coverage. All models include state and month-year fixed effects, and state level controls as discussed in the text and are estimated using sample weights. Standard errors, corrected for clustering at the state level, are reported in parentheses. The signs *, **, and *** represent statistical significance at 10, 5, and 1 percent significance levels.

Table A6. The effect of the UPPLs on alcohol consumption by educational attainment

	High school grad.		Some college grad.		College grad. / Post grad.	
	TWFE	TSDID	TWFE	TSDID	TWFE	TSDID
Consumed alcohol						
Prohibit	-0.000	0.015	0.003	0.031*	0.001	0.020
	(0.006)	(0.013)	(0.006)	(0.019)	(0.004)	(0.017)
No Law	-0.015**	0.103	0.005	0.173***	-0.009	0.106*
	(0.007)	(0.072)	(0.006)	(0.054)	(0.006)	(0.062)
No. of Obs.	1064801	1064801	1210299	1210299	1765932	1765932
Sample mean	0.518	0.518	0.597	0.597	0.690	0.690
Engaged in binge drinking						
Prohibit	0.010**	0.004	0.008*	0.004	0.001	-0.004
	(0.004)	(0.008)	(0.004)	(0.008)	(0.003)	(0.005)
No Law	-0.010*	0.015	0.008*	0.020	-0.001	-0.031
	(0.005)	(0.045)	(0.005)	(0.039)	(0.004)	(0.026)
No. of Obs.	1052768	1052768	1200182	1200182	1755495	1755495
Sample mean	0.192	0.192	0.199	0.199	0.181	0.181
No. of days consumed alcohol						
Prohibit	-0.011	-0.124	0.036	0.125	-0.006	0.255
	(0.064)	(0.114)	(0.093)	(0.152)	(0.064)	(0.243)
No Law	-0.160*	-0.878	0.149**	0.765	-0.026	1.653
	(0.085)	(0.869)	(0.073)	(0.914)	(0.082)	(1.018)
No. of Obs.	1060524	1060524	1206266	1206266	1761377	1761377
Sample mean	4.094	4.094	4.670	4.670	5.982	5.982
No. of days engaged in binge drinking						
Prohibit	-0.018	-0.059	0.000	-0.054	-0.001	-0.042
	(0.020)	(0.053)	(0.017)	(0.053)	(0.013)	(0.044)
No Law	-0.109***	-0.090	0.013	-0.025	-0.002	-0.302
	(0.038)	(0.332)	(0.023)	(0.259)	(0.022)	(0.246)
No. of Obs.	1052768	1052768	1200182	1200182	1755495	1755495
Sample mean	0.887	0.887	0.802	0.802	0.576	0.576
Average number of drinks per day						
Prohibit	-0.005	-0.012	-0.005	0.005	0.005	0.036
	(0.013)	(0.027)	(0.012)	(0.027)	(0.010)	(0.036)
No Law	-0.005	-0.037	0.015	0.228	0.009	0.187
	(0.018)	(0.197)	(0.009)	(0.157)	(0.012)	(0.189)
No. of Obs.	1050787	1050787	1197498	1197498	1752929	1752929
Sample mean	0.452	0.452	0.440	0.440	0.431	0.431

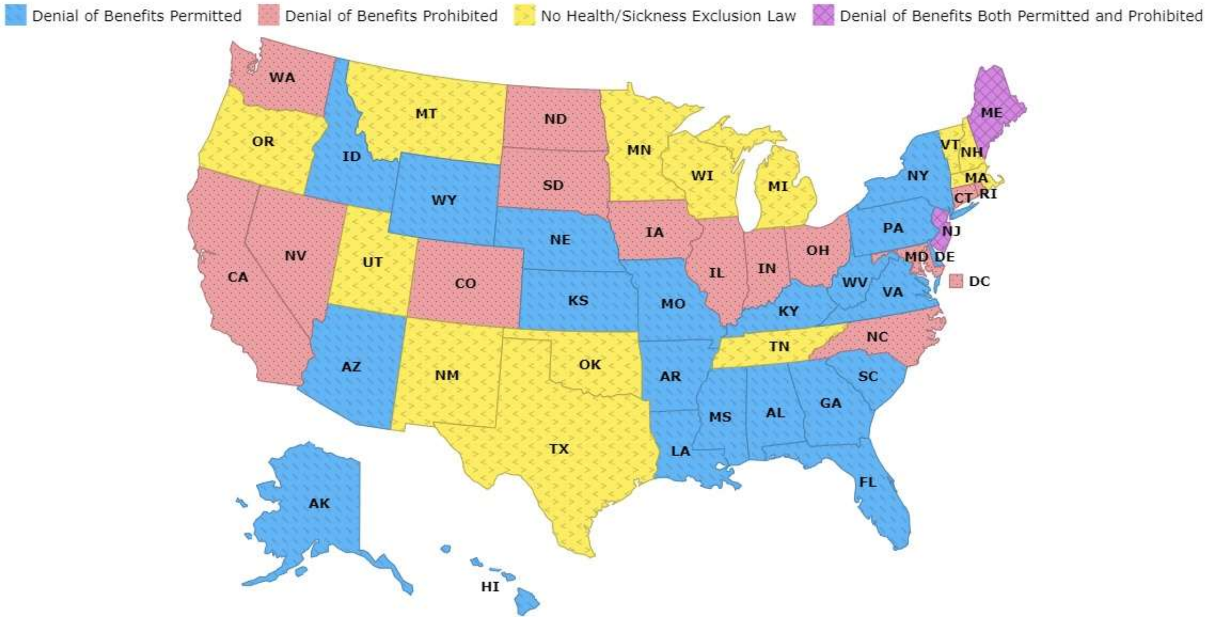
Notes: Sample includes those who are under 65 and have health insurance coverage. All models include state and month-year fixed effects, and state level controls as discussed in the text and are estimated using sample weights. Standard errors, corrected for clustering at the state level, are reported in parentheses. The signs *, **, and *** represent statistical significance at 10, 5, and 1 percent significance levels.

Table A7. The effect of the UPPLs on alcohol consumption outcomes: Results for alternative subsamples of those who drunk at least once at a given month

	TWFE			TSDID		
	Main sample	Female	Male	Main sample	Female	Male
Engaged in binge drinking						
Prohibit	0.008**	0.012***	0.005	-0.008	0.002	-0.015
	(0.004)	(0.003)	(0.005)	(0.012)	(0.011)	(0.015)
No Law	0.004	0.010**	-0.001	-0.056	-0.035	-0.068*
	(0.005)	(0.005)	(0.005)	(0.034)	(0.053)	(0.041)
No. of Obs.	2435897	1290356	1145369	2435897	1290356	1145369
Sample mean	0.318	0.236	0.388	0.318	0.236	0.388
No. of days consumed alcohol						
Prohibit	-0.004	0.011	-0.014	-0.100	-0.126	-0.067
	(0.066)	(0.069)	(0.093)	(0.171)	(0.185)	(0.214)
No Law	0.034	0.104	-0.012	-0.626	-0.914	-0.346
	(0.073)	(0.078)	(0.087)	(1.068)	(1.337)	(1.007)
No. of Obs.	2458885	1300377	1158330	2458885	1300377	1158330
Sample mean	8.191	6.819	9.352	8.191	6.819	9.352
No. of days engaged in binge drinking						
Prohibit	-0.008	0.047***	-0.052*	-0.090	0.025	-0.180*
	(0.016)	(0.016)	(0.026)	(0.057)	(0.036)	(0.094)
No Law	-0.027	0.088**	-0.116***	-0.328	0.015	-0.599
	(0.023)	(0.033)	(0.039)	(0.242)	(0.233)	(0.385)
No. of Obs.	2435897	1290356	1145369	2435897	1290356	1145369
Sample mean	1.261	0.744	1.700	1.261	0.744	1.700
Average number of drinks per day						
Prohibit	-0.003	0.004	-0.008	0.009	0.042	-0.015
	(0.015)	(0.010)	(0.022)	(0.047)	(0.032)	(0.070)
No Law	0.017	0.025**	0.013	0.099	0.258	-0.015
	(0.014)	(0.010)	(0.020)	(0.259)	(0.176)	(0.330)
No. of Obs.	2429112	1286764	1142177	2429112	1286764	1142177
Sample mean	0.742	0.482	0.964	0.742	0.482	0.964

Notes: Sample includes those who are under 65 and have health insurance coverage. All models include individual and state level controls, state, and month-year fixed effects and are estimated using sample weights. Standard errors, corrected for clustering at the state level, are reported in parentheses. The signs *, **, and *** represent statistical significance at 10, 5, and 1 percent significance levels.

Figure A1. Distribution of the states across the U.S. based on the UPPL status as of 2022



Notes: Source: Alcohol Policy Information System (APIS). Denial of benefits are both permitted and prohibited Maine and New Jersey due to certain exemptions of the UPPL.