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## Repeal of State Laws Permitting Denial of Health Claims Resulting from Alcohol Impairment: Impact on Treatment Utilization

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### Abstract

**Background:** Many states in the U.S. still have Alcohol Exclusion Laws (AELs), which allow insurance companies to deny health claims resulting from alcohol impairment. There are concerns that this form of structural stigmatization affects alcohol treatment-seeking behaviors. We examined the effects of AEL repeal on treatment admissions for alcohol use disorder (AUD).

**Methods:** Data on alcohol treatment admissions from 1992 to 2017 were obtained from the Treatment Episode Data Set. The state-level aggregate number of treatment admissions was derived, including healthcare professional referrals only, self-referrals only, and both self-referral and healthcare professional referrals. The number of treatment admissions by health insurance status (private, public, and uninsured) was also calculated. The study used a difference-in-differences (DID) quasi-experimental design.

**Results:** The DID analysis showed that the number of admissions for alcohol treatment from healthcare professional referrals increased 16% in the AEL repeal states compared to states with AELs or that never had AELs (IRR=1.16, 95% CI=1.07, 1.25). These results were consistent for analysis by payment sources. In particular, treatment admissions from healthcare professional referrals for patients covered by private insurance increased about 38% in states with AEL repeal (IRR=1.38, 95% CI=1.17, 1.64) compared to states without AEL repeal. However, the findings were no longer significant when the state-specific time trends were taken into account.

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**Conclusions:** This study documented that AEL repeal may have had a significant impact on the number of treatment admissions for AUD. These findings suggest that AELs function as a barrier to treatment-seeking behavior.

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## Introduction

The harmful use of alcohol is one of the leading risk factors for premature death and disability, accounting for more than 3 million deaths annually, representing about 5% of all deaths worldwide (World Health Organization, 2019). Besides the public health implications, the economic burden of excessive alcohol use is profound, estimated at \$249 billion in 2010 for the U.S. alone (Centers for Disease Control and Prevention, 2018). Data from the 2019 National Survey on Drug Use and Health showed that 26% of U.S. adults aged 18 and older reported binge drinking in the past month (SAMHSA, Center for Behavioral Health Statistics and Quality., 2019a), and about 14.5 million people aged 12 and older had alcohol use disorder (SAMHSA, Center for Behavioral Health Statistics and Quality., 2019b). The number of ED visits involving alcohol consumption increased 61.6% between 2006 and 2014, with a 272% increase in total costs, from \$4.1 billion to \$15.3 billion.(White et al., 2018)

The 2016 Surgeon General's Report concluded that scientific evidence shows substance use disorders, including AUDs, can be effectively treated. However, the overwhelming majority of those with AUDs never receive treatment (Office of the Surgeon General (US), 2016). Only about 5.9% of adults aged 12 and older with AUD in 2019 received any treatment in the past year (SAMHSA, Center for Behavioral Health Statistics and Quality, 2019c). While prior research points to various factors that influence utilization of treatment services (Cohen et al., 2007; Ilgen et al., 2011; Wang et al., 2005), accumulating evidence suggests that stigmatization of substance use, including alcohol, profoundly influences treatment-seeking behavior (Chartier et al., 2016; Hammarlund et al., 2018; Keyes et al., 2010; Satterlund et al., 2015; Smith et al., 2010). Stigmatization may lead to disparities in the quality of patient care and deter treatment-seeking behaviors (Chartier et al., 2016; Hammarlund et al., 2018; Smith et al., 2010). Globally, a number of studies point to the need to address stigmatization policies and attitudes toward those with substance use disorder (Farhoudian et al., 2020; van Boekel et al., 2013).

One potential mechanism of structural stigmatization is that many states in the U.S. still include Alcohol Exclusion Laws (AELs) as part of their insurance code, ostensibly to discourage problem drinking. These laws allow insurance companies to deny claims for injuries resulting from impairment by alcohol or any narcotic not prescribed by a physician. The laws can be applied to various types of insurance, including accident, auto, disability, and health. The relevant insurance arenas are complex, varying both by type of insurance and across states. In this paper, we focus on health insurance, which, in the U.S., is provided by a mix of public and private for-profit and private nonprofit insurers, regulated by both state and federal law. Over two-thirds (67%) of the U.S. population is covered by private insurance, of which two-thirds (amounting to 55% of the population) is employer-sponsored. Except for employers that self-fund their health insurance, state law governs the terms of private insurance coverage (Tikkanen et al., 2020). AELs are one such law. Even when a

state law does not directly govern a particular part of the insurance market, repealing the law can be expected to have “spill-over” effects by causing insurers to rewrite policies for a core part of their business in a way that also influences how they write or administer policies not directly governed by a law.

Although discouraging problem drinking was the primary goal of AELs, a national survey found that many state insurance commissioners noted that people continue to put themselves in harm’s way by drinking alcohol intentionally (Rivara et al., 2000). Moreover, evidence suggests that these laws have significant unintended consequences by creating a disincentive for physicians to test blood alcohol levels of injured patients out of concern that this will trigger reimbursement denials by insurance companies (Rivara et al., 2000; Schermer et al., 2003). Even if insurers do not consistently impose or enforce alcohol exclusions, the fact that they are entitled to do so can have a strong inhibiting effect on care providers. Accordingly, a key stakeholder, the National Association of Insurance Commissioners, changed its position in 2001 to support health insurance coverage regardless of intoxication status. However, many states continue to have AELs. The number of states with AELs peaked in 2000, when 40 states had such laws; since that time, 20 states plus the District of Columbia have repealed their AELs (NIAAA’s Alcohol Policy Information System, 2020).

Largely absent from the extant literature is any examination of the impact of the repeal of these laws. To address this gap, the current study exploits the variation in the timing of the repeal as a natural experiment to examine whether state AEL repeal increases the treatment admissions for AUDs. A prior AEL descriptive analysis among trauma surgeons found that most care providers (82%) are willing to provide alcohol screening and intervention services if there were no insurance barriers, and 24% had experienced an alcohol-related insurance denial in the past six months (Gentilello et al., 2005). Additionally, we examined the heterogeneity of these impacts by payment source (i.e., health insurance type) (Greene et al., 2010; Hazlitt et al., 2014; Lee et al., 2017). We hypothesize that repealing AELs will increase alcohol treatment admissions through reduced stigma and/or referral from healthcare professionals resulting from more BAC testing.

## Methods

### Data sources

Data on treatment service utilization were drawn from the Treatment Episode Data Set (TEDS) from 1992 to 2017. TEDS is an administrative national data system maintained by the Substance Abuse and Mental Health Services Administration (SAMHSA) to track annual admissions and discharges to public and private substance use disorder facilities receiving government funding (Wolfson et al., 2020). Treatment facilities in all states receiving funds provide data on all clients, regardless of health insurance status. Treatment admissions record is routinely collected by state administrative systems and then submitted to SAMHSA for processing. The TEDS system includes about 1.5 million admissions annually due to substance use disorder treatment. TEDS collects clients’ demographic data, including treatment service characteristics and setting, employment status, and insurance status. Additionally, three (primary, secondary, and tertiary) substances of abuse that led to

treatment admission and a source of referral (including a doctor or healthcare provider, self, or criminal justice system) are recorded for each admission.

## Measures

The state-level aggregate number of treatment admissions in which alcohol was recorded as the primary substance use disorder was derived for (i) admissions from healthcare professional referrals, (ii) admissions from self-referrals, and (iii) the total number of admissions from both self-referral and healthcare professional referrals. Additionally, we used a broader outcome for the state-level aggregated number of treatment admissions in which alcohol was recorded as the primary, secondary, or tertiary diagnosis of substance use disorder. To assess the heterogeneity of AEL repeal impact, we derived the number of treatment admissions by health insurance status (private, public, and uninsured).

Our main independent variable was the repeal of AELs, based on data from the NIAAA's Alcohol Policy Information System (APIS) complemented by our legal analysis of state health insurance codes. This variable equals 0 for years with no repeal and 1 for states in which repeal was in effect the entire year. For states with a partial year repeal, we assigned a proportionate fractional value. For example, in a state where the repeal date was effective October 2007, the policy indicator would be operationalized as  $3/12 = 0.25$  for that year and 1 for 2008 and subsequent years. Additionally, vectors of state-level characteristics that vary by state and time were collected, including unemployment rate, insurance coverage rate, the log of state personal income per capita, log of population, mean age, percentage of the state population that is non-Hispanic White, percentage of the state population that is male, blood alcohol concentration laws, and state beer taxes (inflation-adjusted). The insurance coverage rate is the proportion of the population covered by any insurance for each state, which was obtained from the U.S. Census Bureau. We followed the U.S. Census Bureau's recommendation and used the Current Population Survey Annual Social and Economic Supplement (CPS ASEC) data to estimate 2001–2007 insurance coverage and American Community Survey (ACS) data to estimate the insurance coverage rate after 2007. These two estimates differ slightly, but the trend is parallel between 2009 and 2012 (Census Bureau, n.d.) We obtained state unemployment rates (Bureau of Labor statistics, n.d.a) and median household income (in thousand dollars) (Bureau of Labor Statistics, n.d.b) for each state from the Bureau of Labor Statistics, and state alcohol taxes from the tax policy center. (Tax policy Center, 2018) Additional state-level characteristics, including the log of the population, mean age, percentage of the state population that is male, and percentage of the population that is white were calculated using U.S. Population Data from the National Cancer Institute (National Cancer Institute, n.d.) The inflation-adjusted beer excise tax was measured in each state at the 2018 price level. The blood alcohol concentration laws was derived as a binary variable (0.08 g/dL or 0.10 g/dL) based on the BAC limit for a violation for adults operating noncommercial motor vehicles in each state for a given year.

## Statistical analysis

For each year, we plotted the unconditional mean estimates for state-level aggregate number of treatment admissions in which alcohol was the primary substance of abuse between states in three legal categories: 1) states with AELs, 2) states that never had AELs; and 3) states

that repealed AELs. The generalized difference-in-differences (DID or double difference) framework was used to assess the impact of repealing AELs on the number of treatment admissions. Specifically, we used the timing of state AEL repeals to estimate the DID model in an exponential form. Using Poisson regression models, the flow into treatment admissions for a state annually was expressed as a function of the repeal of AELs, vector of state/time-varying characteristics, and state and year-fixed effects (Model 1). Two-way fixed effects (state and year fixed-effects) were included to account for unobserved time-invariant confounding influences within a state as well as common shocks or secular trends. Vectors of state-level characteristics that vary by state and time included the unemployment rate, the percentage of state population with health insurance, the log of median household income, the log of population, mean age, percentage of the state population that is male, percentage of the state population that is white, blood alcohol concentration laws, and state beer taxes (inflation-adjusted). Model 2 changed the function of the variable by using year in continuous form rather than a categorical year, as in Model 1. This functional form allows for a check on the sensitivity of results to Model 3 specification. Model 3 is added as an alternative check on the standard DID model by adding the interaction between state and year to Model 2. This additional component represents unobserved state-specific heterogeneity that evolves at a constant smooth function. It permits states to have a unique time trend, and with adequate data and clear trends, a model with state-specific trends may yield more robust results (Angrist & Pischke, 2008; Besley & Burgess, 2004). We used the R package *sandwich* to obtain robust standard errors for the parameter estimates to control for mild violation of the Poisson distribution assumption that the variance equals the mean (Cameron & Trivedi, 2010; Cameron & Trivedi, 2013). Similar analyses were conducted for the number of treatment admissions by health insurance status (private, public, and uninsured).

### Sensitivity Analyses

Several additional analyses were conducted. First, we repeated our main analyses with broader outcome variables of alcohol-related treatment admissions, which included any alcohol involvement, whether primary, secondary, or tertiary. Second, we conducted two analyses with different age groups (25 and older, 25 to 54) to identify any age-group-specific effects. Third, separate analyses were done using alternative control conditions by excluding states that never had AELs. Doing so removes the legal ambiguity created by the fact that, when state laws are silent on AELs, insurance companies are not necessarily precluded from issuing contracts with an exclusionary intoxication clause. (Oliver BISHOP, III and Oliver Bishop, IV, Plaintiffs-Appellees, v. NATIONAL HEALTH INSURANCE COMPANY, Defendant-Appellant., 2003) Fourth, additional analyses were conducted by changing the treatment condition (states with specific AEL repeal). Specifically, four states (Montana, Tennessee, Texas, and Vermont) that simply deleted alcohol exclusions from their insurance codes were not considered treatment states. Finally, we used a complementary analytical approach (event-level study) to assess preexisting common trends between treatment and control states, as well as to trace out the dynamic or delayed effects of these repeals. Specifically, we replaced the policy variable with the following set of policy dummy variables that reflect whether the state-specific observation is 2-years before the repeals, 1-year prior, the year of the repeals (contemporary effect), 1-year after, 2-years after, 3-years

or more after. The statistical test of the leads (AEL repeal, which captures anticipatory effects) in our model will provide evidence of whether there are differences in preexisting trends between treatment and control states (parallel trend assumption of DID). This will help detect any possible policy endogeneity. The addition of lags (post-repeal) will allow for delayed or heterogeneous repeal effects over time (Angrist & Pischke, 2008; Sabia et al., 2017). Additionally, the lags will enable us to assess whether the effects of the repeals are different between early and late adopters. All analyses were performed using R 4.0.

## Results

Figure 1 presents the unconditional mean estimates of the state aggregate number of treatment admissions for alcohol by AEL status of states (i.e., states with AELs, states that never had an AEL, and states that repealed AELs). The visual display provides suggestive evidence of non-violation of the parallel trend assumption of DID model. The parallel trend assumption assumes that in the absence of treatment (AEL repeal in our case), the difference between the treatment and control group is constant over time. Additionally, the unconditional mean estimates show a marked difference in the flow into alcohol-related treatment admissions, indicating that the repeal of AELs potentially increased the number of alcohol-related treatment admissions. Table 1 shows the results from the DID model analysis of the estimated impact of AEL repeal on the number of alcohol-related treatment admissions, 1992–2017. In Model 1, adjusting for two-way fixed effects (states and year fixed-effects) and other covariates, the repeal of AELs had a 16% increase in the number of admissions for alcohol from healthcare professional referrals compared to those states with AELs or that never had AELs (IRR=1.16, 95% CI=1.07, 1.25). Adjusting for state fixed-effects, year in continuous form, and a vector of state controls (Model 2), we found a similar increase in the number of alcohol-related treatment admissions after the repeal of AELs (IRR =1.13, 95% CI=1.05, 1.23). There was no significant effect of the repeal of AEL in Model 3, which extends Model 2 by allowing for state-specific time trends. The impact of AEL repeal was not significant on the number of alcohol treatment admissions from self-referrals and a combination of both sources (healthcare professionals and self-referrals), except for a decrease in Model 3 for self-referral flow (IRR =0.87, 95% CI=0.78, 0.97).

Table 2 reports the estimated impact of the repeal of AELs on the number of admissions by the source of payment (health insurance status). The number of alcohol treatment admissions from healthcare professional referrals for patients covered by private health insurance increased significantly. In particular, treatment admissions increased over 26% in states with AEL repeal compared to control states (those without AEL repeal) (Model 1, IRR=1.38, 95% CI=1.17, 1.64; Model 2, IRR=1.26, 95% CI=1.08, 1.47). Similar results were found for other insurance payment sources (public and uninsured) regardless of the referral source.

The results of sensitivity analyses are shown in Table 3 and Supplementary Tables 1–5. The findings in the sensitivity analyses using broader outcome variables of alcohol-related treatment admissions were largely consistent with the main analyses (Table 3). States with AEL repeal had 38% more referrals for alcohol-related treatment admissions from healthcare professionals (Model 1) than control states. In the event-level analysis, the lead

indicators (2-year and 1-year before the AEL repeal) had no significant impact on the number of alcohol admissions from healthcare professionals or self-referrals (Supplementary Table 1). Consistent with the visual display (Figure 1), these results indicate that our main findings are not due to changes in trends that occurred before the repeals of AELs (parallel trend assumption of DID does not appear to be violated). A lagged indicator of 3 or more years post-AEL repeal significantly impacted alcohol treatment admissions for healthcare professional referrals and both sources (self and healthcare professional referrals). This suggests that the AEL repeal had a persistent effect on the number of alcohol admissions. We also found that the results were similar in both age groups (25 and older, 25 to 54) (Supplementary Tables 2 and 3). The results in the analysis with different control states (excluding states that never had AELs) and treatment states (whether states specifically repealed AELs) were also consistent with the results of the primary analyses (Supplementary Tables 4 and 5).

## Discussion

Concerns about the consequences of AELs have been voiced by many stakeholder organizations (e.g., American College of Surgeons, 2006; American Medical Association, 2016; American Public Health Association, 2004; American Society of Addiction Medicine, 2005), along with calls for their repeal. One such concern is that these laws may discourage healthcare professionals from referring their patients to alcohol treatment services. The effects of AELs and their repeal are not well understood, given the limited extant literature. This study addresses this gap by examining whether the repeal of these laws affects the utilization of alcohol treatment services. The study provides evidence that AEL repeal increased the number of treatment admissions for alcohol use disorder for referrals from healthcare professionals. Findings were consistent in analyses by sources of payment for treatment. The event-level study also suggested that the increase in alcohol admissions persisted over time.

Our results for alcohol treatment admissions from self-referrals, for the most part, showed no significant effects of the repeal of AELs; however, that finding varied by insurance payment source. AEL repeal's effect on alcohol treatment utilization was significant for two insurance payment sources (public and uninsured). To what extent AEL repeal influenced alcohol-related stigma remains unknown. The mixed findings for the number of self-referred treatment admissions, in part, could be due to there being little or no change in the total level of stigma associated with AUDs in the U.S. (Chartier et al., 2016; Pescosolido et al., 2010). Concerns about being viewed negatively by others (i.e., the internalization of public stigma) and self-stigma have been well documented as significant barriers to someone admitting that a problem with AUDs exists or that treatment- is needed (Edlund et al., 2006; Mojtabai et al., 2014; Saunders et al., 2006). Effective strategies to reduce other aspects of stigma are needed to increase further the utilization of treatment for AUDs (Wogen & Restrepo, 2020).

It is worth noting two possible AEL legal operationalization considerations in the interpretation of our findings. First, simply repealing these statutes did not prohibit the use of the AEL clause in insurance policies. Instead, simple repeal primarily removed restrictions on how these clauses can be worded – thus having a more permissive legal



effect(Oliver BISHOP, III and Oliver Bishop, IV, Plaintiffs-Appellees, v. NATIONAL HEALTH INSURANCE COMPANY, Defendant-Appellant., 2003). Second, there is potential heterogeneity in how AELs are interpreted or enforced across states. Finally, a statutory condition that plausibly could have a greater discernable effect is when a state expressly prohibits using an AEL clause, and whether such a prohibition covers types of insurance beyond health insurance, such as accident, disability, and life insurance. Future studies could provide more understanding of the impact of AELs by examining clause-specific AEL dimensions. Additionally, the non-significant findings in models with state-specific time trends could be attributable to the added component (time varying state trend) reducing time variation in state AEL repeal variable, which causes identification issues that preclude jointly estimating treatment effects and capturing state-specific trends.

This study has several limitations. First, due to the nature of TEDS (precautions to ensure anonymity), some of those admitted to treatment facilities could have been double-counted if they returned for another round of treatment. Second, while fixed-effect models were used to adjust for time-invariant characteristics of each state and state-invariant time effects, there may be important time- and state-varying confounders not captured in our models. However, we extended our fixed-effect models to allow state-specific time trends in one of the specifications and found non-significant result. Third, the study is limited to treatment admissions reported to TEDS, excluding patients who receive treatment from providers who do not report to TEDS.

## Conclusions

To our knowledge, this is the first quantitative study that comprehensively evaluates alcohol exclusion laws. The proposed research addresses a highly understudied area of high public health significance: the potential of health insurance system-level factors--such as AELs--to function as large, unrecognized, and significant barriers to receiving treatment for AUDs. The current study documented that AEL repeal increased the number of treatment admissions for alcohol use disorder significantly, especially for referrals from healthcare professionals. These impacts were consistent across different payment sources. However, the results did not hold up when the state-specific time trends were taken into account, suggesting the need for further research to evaluate state-specific dimensions of AELs.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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## Role of the Funder/Sponsor

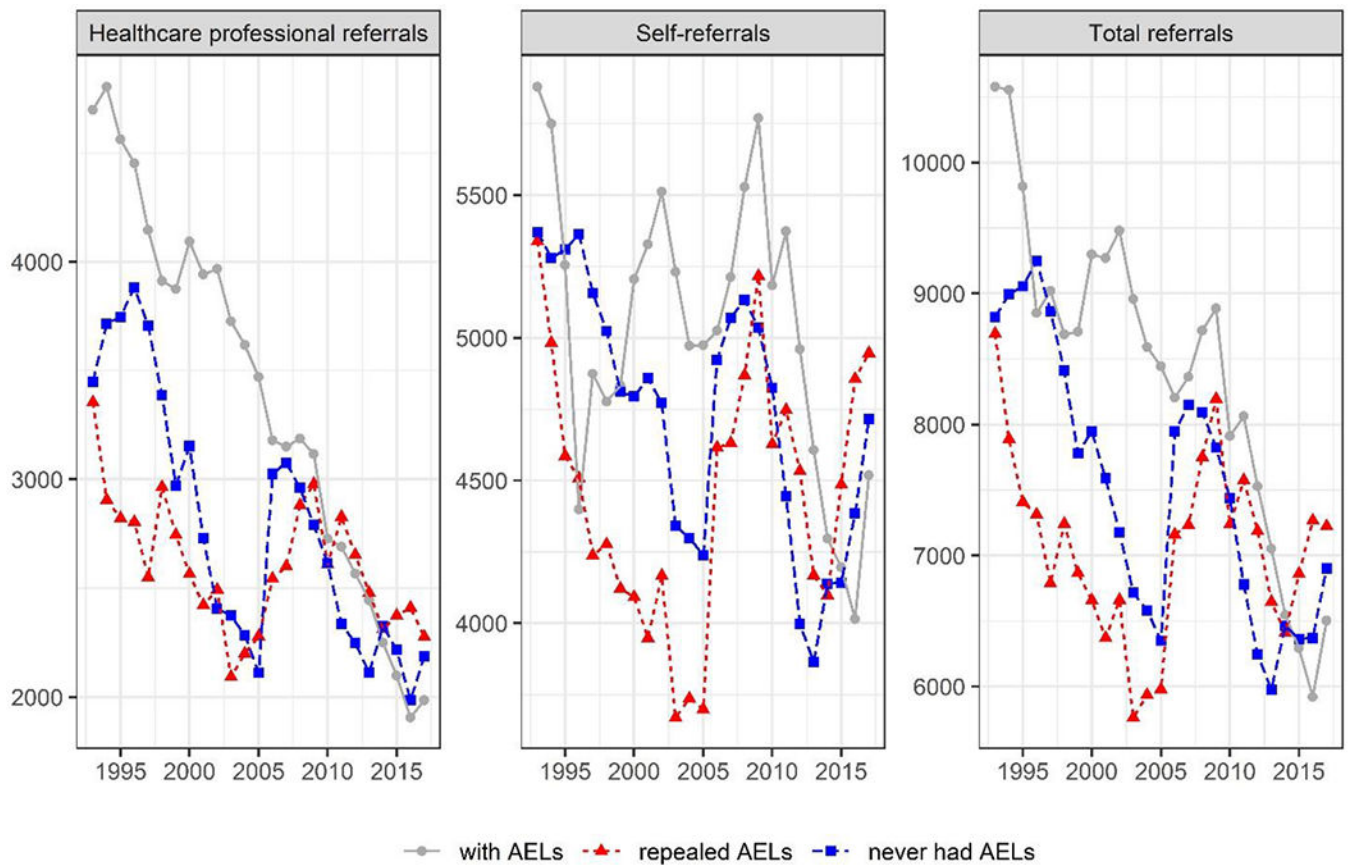
The sponsors had no role in the design and conduct of the study, collection, management, analysis, and interpretation of the data, preparation, review, or approval of the manuscript, and decision to submit the manuscript for publication.

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**Figure 1:**

Mean estimates of state-level aggregate number of treatment admissions, 1992-2017

<sup>a</sup>The state-level aggregate number of treatment admissions in which alcohol was the primary substance of abuse for patients aged at least 18 years old.

<sup>b</sup>Total referrals refer to total number of admissions from both self-referral and healthcare professional referrals.

**Table 1:**

The estimated impact of the repeal of AELs on number of admissions for alcohol, 1992-2017

Number of admissions <sup>a</sup>	Model 1 <sup>b</sup>	Model 2 <sup>c</sup>	Model 3 <sup>d</sup>
Healthcare professional referrals	<b>1.16(1.07, 1.25)</b>	<b>1.13(1.05, 1.23)</b>	0.98(0.88, 1.09)
Self-referrals	0.99(0.91, 1.06)	0.97(0.89, 1.06)	<b>0.87(0.78, 0.97)</b>
Self-referral and healthcare professional referrals	1.05(0.98, 1.13)	1.04(0.96, 1.11)	0.91(0.83, 1.01)

<sup>a</sup>The state-level aggregate number of treatment admissions in which alcohol was the primary substance of abuse for patients aged at least 18 years old.

<sup>b</sup>Model 1 adjusted for two-way fixed effects (state and year fixed effects).

<sup>c</sup>Model 2 adjusted for state fixed effects and year in the continuous form.

<sup>d</sup>Model 3 added an interaction between state and year to Model 2 to allow states to have a unique time trend.

<sup>e</sup>Boldface indicates statistical significance ( $p < 0.05$ ).

<sup>f</sup>Incidence risk ratio and its 95% confidence interval were presented. In each Poisson regression models, we controlled for a vector of state-level characteristics, including unemployment rate, insurance coverage rate, log of state personal income per capita, log of population, mean age, percentage of the state population that is non-Hispanic White, percentage of the state population that is male, blood alcohol concentration laws, and state beer taxes (inflation-adjusted).

**Table 2:**

The estimated impact of the repeal of AELs on number of admissions for alcohol by health insurance status, 1992-2017

Number of admissions <sup>a</sup>	Health insurance status	Model 1 <sup>b</sup>	Model 2 <sup>c</sup>	Model 3 <sup>d</sup>
Healthcare professional referrals	Private	<b>1.38(1.17, 1.64)</b>	<b>1.26(1.08, 1.47)</b>	1.14(0.92, 1.41)
	Public	<b>1.42(1.19, 1.71)</b>	<b>1.37(1.14, 1.64)</b>	1.05(0.79, 1.38)
	Uninsured	<b>1.35(1.16, 1.57)</b>	<b>1.30(1.13, 1.51)</b>	0.99(0.87, 1.12)
Self-referrals	Private	1.06(0.87, 1.29)	1.04(0.86, 1.27)	0.92(0.79, 1.08)
	Public	<b>1.88(1.55, 2.27)</b>	<b>1.77(1.47, 2.13)</b>	1.05(0.82, 1.34)
	Uninsured	<b>1.24(1.10, 1.41)</b>	<b>1.20(1.06, 1.36)</b>	0.90(0.78, 1.04)
Self-referral and healthcare professional referrals	Private	1.17(0.98, 1.41)	1.13(0.95, 1.34)	1.01(0.86, 1.19)
	Public	<b>1.65(1.38, 1.96)</b>	<b>1.57(1.32, 1.86)</b>	1.04(0.82, 1.33)
	Uninsured	<b>1.27(1.13, 1.42)</b>	<b>1.22(1.09, 1.37)</b>	0.93(0.83, 1.05)

<sup>a</sup>The state-level aggregate number of treatment admissions in which alcohol was the primary substance of abuse for patients aged at least 18 years old.

<sup>b</sup>Model 1 adjusted for two-way fixed effects (state and year fixed effects).

<sup>c</sup>Model 2 adjusted for state fixed effects and year in the continuous form.

<sup>d</sup>Model 3 added an interaction between state and year to Model 2 to allow states to have a unique time trend.

<sup>e</sup>Boldface indicates statistical significance ( $p < 0.05$ ).

<sup>f</sup>Incidence risk ratio and its 95% confidence interval were presented. In each Poisson regression models, we controlled for a vector of state-level characteristics, including unemployment rate, insurance coverage rate, log of state personal income per capita, log of population, mean age, percentage of state population that is non-Hispanic White, percentage of state population that is male, blood alcohol concentration laws, and state beer taxes (inflation-adjusted).

**Table 3:**

The estimated impact of the repeal of AELs on number of admissions for alcohol using broader definition<sup>a</sup> by health insurance status, 1992-2017

Number of admissions <sup>a</sup>	Health insurance status	Model 1 <sup>b</sup>	Model 2 <sup>c</sup>	Model 3 <sup>d</sup>
Healthcare professional referrals	Private	<b>1.38(1.17, 1.62)</b>	<b>1.24(1.06, 1.45)</b>	1.07(0.88, 1.32)
	Public	<b>1.29(1.09, 1.52)</b>	<b>1.23(1.04, 1.46)</b>	0.96(0.75, 1.23)
	Uninsured	<b>1.34(1.16, 1.54)</b>	<b>1.29(1.13, 1.48)</b>	1.01(0.88, 1.17)
Self-referrals	Private	1.03(0.85, 1.25)	1.01(0.84, 1.22)	0.86(0.73, 1.03)
	Public	<b>1.59(1.33, 1.90)</b>	<b>1.50(1.26, 1.79)</b>	0.96(0.76, 1.21)
	Uninsured	<b>1.21(1.07, 1.37)</b>	<b>1.17(1.03, 1.32)</b>	0.93(0.80, 1.09)
Self-referral and healthcare professional referrals	Private	1.15(0.96, 1.38)	1.11(0.93, 1.32)	0.95(0.81, 1.13)
	Public	<b>1.44(1.22, 1.69)</b>	<b>1.37(1.16, 1.62)</b>	0.95(0.76, 1.19)
	Uninsured	<b>1.24(1.11, 1.39)</b>	<b>1.20(1.07, 1.34)</b>	0.96(0.84, 1.10)

<sup>a</sup>The state-level aggregate number of treatment admissions in which alcohol was the primary, secondary, or tertiary diagnosis of substance abuse for patients aged at least 18 years old.

<sup>b</sup>Model 1 adjusted for two-way fixed effects (state and year fixed effects).

<sup>c</sup>Model 2 adjusted for state fixed effects and year in the continuous form.

<sup>d</sup>Model 3 added an interaction between state and year to Model 2 to allow states to have a unique time trend.

<sup>e</sup>Boldface indicates statistical significance (p<0.05).

<sup>f</sup>Incidence risk ratio and its 95% confidence interval were presented. In each Poisson regression models, we controlled for a vector of state-level characteristics, including unemployment rate, insurance coverage rate, log of state personal income per capita, log of population, mean age, percentage of the state population that is non-Hispanic White, percentage of the state population that is male, blood alcohol concentration laws, and state beer taxes (inflation-adjusted).